CESifo WORKING PAPERS

11034
2024

March 2024

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CESifo

Impressum:

CESifo Working Papers
ISSN 2364-1428 (electronic version)
Publisher and distributor: Munich Society for the Promotion of Economic Research - CESifo GmbH
The international platform of Ludwigs-Maximilians University's Center for Economic Studies and the ifo Institute
Poschingerstr. 5, 81679 Munich, Germany
Telephone +49 (0)89 2180-2740, Telefax +49 (0)89 2180-17845, email office@cesifo.de
Editor: Clemens Fuest
https://www.cesifo.org/en/wp
An electronic version of the paper may be downloaded
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CESifo *Working Paper No. 11034*

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Abstract

Inequality between ethnic groups has been shown to be negatively related to GDP, but research on its effect on contemporary economic growth is limited by the availability of comparable data. We compile a novel and comprehensive dataset of harmonized Gini indices on ethnic inequality for countries and sub-national units between 1992 and 2013. Our approach exploits differentials in nighttime lights (NTL) across ethnic homelands, using new techniques to harmonize NTL series across geographic regions and years to address concerns about spatial and temporal incomparability of satellite photographs. Our new data shows that ethnic inequality is widespread across countries but has decreased over time. Exploiting the artificiality of sub-national borders in an instrumental variable setting, we provide evidence that income inequality across ethnic groups reduces contemporary economic growth. The negative effect of ethnic inequality is caused by increasing conflict and decreasing public goods provision.

JEL-Codes: O100, O150, O430.

Keywords: ethnic inequality, economic development, regional data, nighttime lights, satellite photographs, calibration, ethnic groups, conflict, public goods provision.

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March 24, 2024
We are grateful for constructive feedback and comments from Toke Aidt, Christine Binzel, Christian Bjørnskov, Richard Bluhm, Eve Colson-Sihra, Raphael Franck, Victoire Girard, Jerg Gutman, Andreas Haufler, Arye Hillman, Roland Hodler, Lennart Kaplan, Marko Köthenburger, Dominika Langenmayr, Christian Leßmann, Martin Paldam, Niklas Potrafke, Hillel Rapoport, Mathias Thoenig, Kaspar Wüthrich, and Noemie Zurlinden. We would also like to thank seminar participants at the 28th Silvaplana Workshop on Political Economy 2020 in Pontretsina, the 8th Meeting of the Society for the Study of Economic Inequality (ECINEQ) 2019 in Paris, the 2019 Annual Meeting of the European Public Choice Society (EPCS) in Jerusalem, the 3rd International Conference on the Political Economy of Democracy and Dictatorship (PEDD) in Muenster, the 2019 Annual International Conference of the German Economic Association Research Group on Development Economics in Berlin, the 2nd Workshop on GeoData in Economics in Hamburg, the 27th BGPE Workshop in Munich, and the 13th CESifo Workshop on Political Economy in Dresden for very valuable discussions. We would also like to thank participants at research seminars at the FAU Erlangen-Nürnberg, the ifo Institute Munich and the LMU Munich for valuable feedback and discussion.

1 Introduction

The question of whether ethnicity matters for economic development has been examined by many scholars in the social sciences. A vast literature has shown that ethnolinguistic fragmentation negatively affects economic growth, e.g. by increasing corruption and conflict (Mauro, 1995; Montalvo and Reynal-Querol, 2005a; Esteban et al., 2012; Arbatli et al., 2020) and by decreasing levels of education and the quality of institutions (Easterly and Levine, 1997; Alesina et al., 2003). An important and largely unconsidered question is whether these effects are initiated by the sheer coexistence of ethnic groups or by an unequal concentration of well-being across groups ("ethnic inequality"). Recent research has used the distribution of nighttime luminosity across ethnic homelands to measure economic differences between ethnic groups (Alesina et al., 2016). While this approach has revealed important insights about a negative cross-sectional relationship between ethnic inequality and economic development, it remains an open question whether ethnic inequality affects current growth rates of per capita GDP. Is the relationship between ethnic inequality and per capita GDP driven by historical factors whose importance declined with the transition to modernity? If so, the negative correlation might mainly be inherited from developments in the distant past. Or has the relationship strengthened over time and continues to affect countries' growth rates today?

This paper provides first evidence for a robust negative effect of ethnic inequality on contemporary economic growth. We combine new techniques from the remote sensing literature to harmonize satellite photographs of nighttime lights (NTL) and demonstrate that corrected NTL deliver more accurate estimates of economic development and its dynamics over time, which is key to construct harmonized longitudinal estimates of inequality across ethnic homelands. We then use our harmonized measures to compile a novel dataset that provides comparable Gini indices of ethnic inequality for the broadest possible sample of countries (189 countries, 4,032 country-year observations) and ADM1 regions (3,609 regions, 66,912 region-year observations), 1992–2013. In addition to creating a 'traditional' measure of ethnic inequality, we also construct a new measure that considers the population sizes of ethnic groups. Both measures suggest a considerable global decline in ethnic inequality between 1992 and 2013 of around 20%. In the empirical analysis, we find that ethnic inequality negatively affects economic growth. This result holds through various modifications of the baseline data and is corroborated by an instrumental variable analysis exploiting the border artificiality of sub-national units in Africa for causal identification. The effect size of the cumulative long-run effect is economically significant—going from a country with an equal distribution of group incomes to a country where all income concentrates at a single group reduces per capita GDP by around 12% to 15%. Lastly, we focus on two mechanisms through which ethnic inequality is related to growth. The results show that it is important to carefully take into account the underlying form of ethnic inequality. While a more unequal distribution of resources across groups is positively related to conflict, it is important to account for the relative population sizes of groups when studying the relationship to public good provision.

Recent research has shown that nighttime light series, while enjoying great popularity in the economics literature as a proxy for economic development, are plagued by temporal-inconsistency and limited comparability on a global scale (Li and Zhou, 2017; Bluhm and Krause, 2022; Zheng et al., 2019; Chiovelli et al., 2023). In this paper, we compile a new dataset of ethnic inequality measures based on adjusted NTL that increase comparability across geographic regions and across time. Our method to measure ethnic inequality follows Alesina et al. (2016) by using satellite images on nighttime lights from the DMSP-OLS program to obtain spatial estimates of per capita incomes for ethnic homelands. NTL provide good proxies for economic activity when the focus is on economic development at a certain point in time (see, e.g., Henderson et al., 2012; Michalopoulos and Papaioannou, 2013; Alesina et al., 2016). However, employing them to measure yearly changes in local economic development comes with severe drawbacks. The satellites that record NTL for the DMSP-OLS program were initially constructed during the 1960s to measure weather conditions for military operations and were never designed to deliver fine-grained estimates of local economic development. The vintage technology of these satellites results in a lack of inter-annual calibration and photographs of the earth at night that are top-coded at a moderate level of luminosity. A further hurdle to comparability is that pictures were taken by several satellites at different stages of sensor degradation. As a consequence, NTL are only comparable to a limited extent across geographic regions and across years (Elvidge et al., 2009; Zhang et al., 2016; Li and Zhou, 2017; Uprety et al., 2017; Chiovelli et al., 2023).

The fundamental building block of our analysis is the construction of a corrected series of per capita luminosity that eliminates the temporal-inconsistency of satellite data and that removes the top-coding of satellite photographs, consolidating new techniques from the remote sensing literature that have been developed only recently (Li and Zhou, 2017; Zheng et al., 2019; Bluhm and Krause, 2022). We demonstrate that correcting NTL substantially increases the accuracy to measure economic development. By adjusting the raw NTL data, the correlation between NTL and GDP increases from 76.19% to 94.41%. In a detailed analysis of cases studies, we show that adjusted NTL also lead to more plausible levels of local economic development. Additionally, we show that ill-calibration and top-coding asynchronously affect ethnic homelands, which cannot be addressed by simply adding period fixed effects in empirical regressions.

Our dataset includes two sets of ethnic inequality measures. The first variant follows the traditional approach and approximates the mean income level of ethnic groups by per capita luminosity of ethnic homelands and computes Gini indices that reflect within-country differences in well-being across ethnic groups. The second variant uses population weights to account for the size of ethnic groups.[1] The non-weighted version, Gini(NW), takes ethnic groups as the unit of observation. Hence, a decrease in Gini(NW) reflects convergence in terms of average group incomes. By accounting for the size of ethnic groups, the population-weighted variant, Gini(W), addresses differences in political power. Both variants reflect certain aspects of ethnic inequality that may transmit differently to growth.

We document two main results. The first main result is that between-group inequality is widespread throughout the world, but there is large heterogeneity in ethnic inequality across space and time. On a global scale, levels of non-weighted ethnic inequality are comparable to officially reported inequality of disposable incomes, but the standard deviation of between-group inequality is larger, suggesting that heterogeneity in ethnic inequality is higher than heterogeneity in personal inequality. While heterogeneity persists when we account for the size of groups,

[1] Relatedly, recent work by Mayoral and Ray (2022) has shown that the size of ethnic groups matters for conflict over private and public goods.

the mean level of population-weighted ethnic inequality is lower than that of our non-weighted variant. Our study also provides first evidence on cross-country trends in ethnic inequality over time. The data suggests that inequality between ethnic groups has considerably decreased between 1992 and 2013, both for weighted (-21.5%) and non-weighted (-16.8%) inequality.

In the second part of our paper, we use our new measures to identify the growth effect of ethnic inequality. We start by providing evidence on the influence of between-group inequality on economic growth at the national level. To this end, we disentangle the confounding influence of past GDP dynamics and time-invariant unobservables in a dynamic panel data model that includes a full set of fixed effects for countries and years. Our setup also accounts for GDP dynamics and non-stationarity in GDP series (Hamilton, 2018; Acemoglu et al., 2019). To tackle threats to identification researchers usually face when working with national data (most importantly the presence of time-varying omitted factors), we use variation in ethnic inequality across first-level administrative regions in Africa. The sub-national perspective allows us to account for time-varying unobservables on the country-level by including fixed effects for country-years. To eliminate time-varying omitted factors on the sub-national level, we exploit the mismatch of sub-national administrative units with the spatial distribution of ethnic homelands ("border artificiality"). We show that 83.24% of ethnic groups included in our dataset are partitioned by sub-national borders, resembling the substantial extent of border artificiality documented for the national level in previous work (see, e.g., Michalopoulos and Papaioannou, 2016). We construct an instrumental variable for sub-national ethnic inequality by computing artificial spatial counterfactuals based on per capita incomes of individuals that belong to ethnicities that are present in a particular sub-national unit, but that live in locations outside this unit ("outside-units"). We show that there is substantial variation in the spatial distribution of ethnicities over outside-units and that inequality between the fraction of ethnicities living outside a particular sub-national unit is correlated with between-group inequality within this unit. As the distribution of ethnic groups over outside units is widespread and often spans several countries, we argue that our artificial spatial counterfactuals do not affect sub-national economic growth through channels other than the narrow causal pathway of influencing ethnic inequality.

Our second main results is that ethnic inequality is an economically and statistically significant predictor of modern economic growth. For the national level, our estimates suggest that a one-standard deviation change in ethnic inequality, which is about the differences between Austria and Nigeria, or between Argentina and Botswana, reduces economic growth by approximately 2.5%. The cumulative long-run effect of a permanent transition from an equal distribution of group incomes to the concentration of all income at a single group is -15.8% of real per capita GDP. These numbers are remarkably close to the effect size found on the sub-national level for Africa, where we find a permanent long-run effect of -12.5%. Our findings are robust to various changes in the construction of our ethnic inequality measures (e.g. excluding small ethnic groups, omitting urban areas, using alternative population data), the inclusion of potential confounding factors as well as other forms of heterogeneity in terms of incomes, population size, or ethnicity. Consistent with previous studies, our results show that considerable parts of the effect work through spurring conflict and through reducing the provision of public goods. The relationship between ethnic inequality and conflict is stronger for Gini(NW), while accounting for the size of ethnic groups is important to reveal the influence of ethnic inequality on public goods provision.

Contribution to the Literature: The main contribution of our paper is to provide first empirical evidence on the effect of inequality between ethnic groups on contemporary economic growth. Our paper connects to the literature on the consequences of inequality across ethnic groups. The first attempt to measure ethnic inequality goes back to Barrows (1976), but interest in research on the causes and consequences of ethnic inequality grew mostly only during the past decade. Since then ethnic inequality has been associated with various determinants of economic development. Many studies have linked ethnic inequality to (civil) conflict (Østby, 2008; Baldwin and Huber, 2010; Cederman et al., 2011; Cederman et al., 2015; Huber and Mayoral, 2019; Lessmann and Steinkraus, 2019). In a similar vein, Houle and Bodea (2017) show that larger levels of ethnic inequality also increase the probability of Coups d'État. Other research established that economic differences between ethnic groups can also affect countries' institutions and political systems (Kyriacou, 2013; Huber and Suryanarayan, 2016). In recent work, Hodler et al. (2020) showed that also norms and values can be affected by ethnic inequality, by linking larger economic differences between ethnic groups to lower levels of trust in their sample of African cities. Finally, Alesina et al. (2016) use a novel approach exploiting differences in nighttime lights between ethnic homelands to construct a new measure of ethnic inequality. The results of their analysis show a strong negative relationship between ethnic inequality and GDP per capita in the year 2000.

This paper contributes to this literature by linking larger levels of ethnic inequality to lower rates of contemporary economic growth. Thereby we show that the link between ethnic inequality and economic development, first shown by Alesina et al. (2016), has been strengthening even further in the last decades. We also demonstrate that, dependent on the research question, it can be important to account for population sizes of groups when computing ethnic inequality measures. Moreover, we provide a new panel dataset that includes comparable measures of ethnic inequality for the broadest possible sample of countries and sub-national regions observed between 1992 and 2013.

Second, this paper relates to the increasing body of research that draws on nighttime lights as a proxy for economic development (e.g. Henderson et al., 2012; Michalopoulos and Papaioannou, 2013; Alesina et al., 2016; see Donaldson and Storeygard, 2016 for a survey). While NTL are good proxies for economic development in many settings, lack of inter-annual calibration and top-coding of luminosity confronts researchers with major challenges when nighttime lights are used to uncover dynamic processes (Li and Zhou, 2017; Bluhm and Krause, 2022; Zheng et al., 2019; Chiovelli et al., 2023). This paper shows how new developments in the remote sensing literature can be used to obtain estimates of comparative economic development that are better comparable across geographic regions and across time than previously used measures. Adjusting nighttime lights series may potentially be important also for other future projects that aim to approximate economic development with nighttime luminosity.

Third, our work is related to the literature examining the drivers of economic growth (Durlauf et al., 2005; Ciccone and Jarocinski, 2010; Moral-Benito, 2012), and, in particular, the growth effect of inequality (Berg et al., 2018) and ethnic fragmentation (Alesina et al., 2003; Alesina and La Ferrara, 2005; Montalvo and Reynal-Querol, 2005a; Montalvo and Reynal-Querol, 2021). We connect to this literature by showing that income differentials across ethnic groups have an economically and statistically significant impact on contemporary economic growth. We also show that this impact materializes through an increase in conflict and a decrease in the provision of public goods. These results imply that ethnic inequality is related differently to growth than household-level or individual-level inequality.

Organization: The remainder of the paper is structured as follows. In Section (2) we introduce our new dataset on ethnic inequality, describe the process of removing spurious elements of nighttime lights and explain how we compute Gini indices of ethnic inequality. A brief discussion of descriptive statistics of ethnic inequality follows. In Section (3), we present our country-level results on the effect of ethnic inequality on economic growth. In Section (4), we present subnational results that allow for a causal interpretation. Section (5) features an analysis of the transmission channels of ethnic inequality. Section (6) concludes.

2 Measuring ethnic inequality

2.1 Overview

When constructing measures of interethnic economic inequality, researchers can choose between two general approaches. The first (traditional) approach is to extract information from social surveys (see, e.g., Østby, 2008; Baldwin and Huber, 2010; Houle and Bodea, 2017), the second (more recent) approach is to exploit geospatial data (Cederman et al., 2011; Cederman et al., 2015; Alesina et al., 2016). While fine-grained micro data is often superior to spatial data in local settings, such data typically does not exist on a global scale. Moreover, combining data from various surveys or constructing inequality measures based on property results in reduced comparability when survey designs are incomparable or unrepresentative on the group-level. Spatial data is also more objective when scholars are confronted with over- or under-reporting, which is often the case in surveys that ask for individuals' incomes (Meyer et al., 2015). The optimal choice of method hence depends on the question researchers aim to answer. Our purpose is to construct a comparable and balanced panel dataset for the broadest possible coverage of countries and years. In the absence of reliable and harmonized micro data, we compute geospatial indices of ethnic inequality by exploiting differentials in nighttime lights (NTL) across geographic homelands of ethnic groups (Alesina et al., 2016).

Summary of our geospatial approach: Our approach consists of three steps. First, we identify the location of ethnic groups using digitized maps. Second, we use geocoded population data and satellite data on nighttime lights to construct per capita luminosity for each ethnic homeland. Third, we compute Gini indices that reflect inequality of per capita luminosity between ethnic homelands. Our final dataset consists of 189 countries (4,032 country-year observations) and 3,609 subnational regions (66,912 region-year observations) for the period 1992–2013.

Incomparability of nighttime lights across space and time: To deliver valid estimates of ethnic inequality, our approach requires granular and comparable data on nighttime luminosity. Many scholars have used nighttime lights to proxy economic development (e.g. Henderson et al., 2012; Michalopoulos and Papaioannou, 2013; Alesina et al., 2016), but per capita luminosity is inaccurate if scholars aim to compare economic development across fine-grained local levels and across time (Li and Zhou, 2017). Satellite photographs are influenced by varied atmospheric conditions, satellite shift or sensor degradation and lack means of on-board calibration to correct for such distortions (Li and Zhou, 2017). Satellites also have limited storage capacity, and hence photographs are top-coded at a luminosity level that has been reached by many cities in developing and advanced economies already decades ago. When computing ethnic inequality based on the spatial distribution of nighttime lights, inequality measures are likely to be biased by the incomparability of the raw nighttime light series. Hence, an important step of our method is to calibrate the raw nighttime lights series and remove their top-coding, achieving adjusted NTL series that are comparable across space and time.

Limitations of the geospatial approach: The geospatial approach faces two limitations. First, migration flows between geographical units may lead to an underestimation of ethnic groups in target countries. Second, ethnic groups often overlap in urban centers. Relying on spatial data hence leaves us with a lower bound estimate of ethnic groups residing in a given geographic unit. We cannot rule out that geographic measures of between-group inequality are affected by conservative estimates of ethnicities, but two arguments give us confidence that there is no systematic bias: (i) ethnic settlement patterns exhibit a considerable degree of inertia (Weidmann et al., 2010b) and (ii) our geospatial measures do not react sensitive to the exclusion of urban areas or ethnic groups with small population size.

In the next steps, we briefly introduce the underlying datasets, provide a detailed discussion on our construction process and our strategy to obtain comparable NTL series, and present descriptive statistics of our ethnic inequality measures.

2.2 Data

Ethnic Group Data: For the spatial identification of ethnic groups, we use the "Geo-Referencing of Ethnic Groups" (GREG) dataset (Weidmann et al., 2010a), which is a digital version of the Soviet "Atlas Narodov Mira" (ANM). The ANM was constructed by Soviet ethnographers in the 1960s and lists a total of 1,248 ethnic groups around the globe. GREG excludes ethnicities that do not possess own homelands and thus lack regional concentration (which applies to 319 groups), and maps 929 groups that are represented by 8,969 geo-referenced polygons. 7,383 of these polygons contain a single ethnicity, while ethnic groups overlap in 1,586 polygons (two ethnic groups in 1,552 polygons and three ethnic groups in 34 polygons). As GREG does not map changing settlement patterns of ethnic groups over time, we additionally employ the GeoEPR dataset (Vogt et al., 2015), which includes these changes. A drawback is that GeoEPR only accounts for a subset of "politically relevant" groups.

Map Data: The country borders in GREG refer to the political situation of the 1960s. We employ the *Digital Chart of the World* (DCW) and the *CShapes* Dataset (Weidmann et al., 2010a) to match the ethnic homelands with current borders. DCW features a very accurate map of country borders, but it is stationary and refers to the year 2000. CShapes, while being less detailed, includes any territorial changes between 1946 and 2017. To avoid the creation of "artificial ethnic groups", i.e. an assignment of groups to countries outside their homeland, we employ both maps and cut off the overlapping territories. This procedure results in a loss of 0.3% of the world population.

Population Data: To measure the population of ethnic homelands, we use the *Gridded Population of the World* (GPW) dataset, version 3 from CIESIN (2004, 2016, 2018a,b) and GHS-POP computed by Freire et al. (2016). GPWv3 is available in five-year steps for the period 1990-2015. It uses input data with grid cell resolution of 2.5 arc-minutes ($\sim$ 5 kilometers at the equator). We interpolate the population data for the period between the observation points. The GHS-POP dataset employs a dasymetric mapping approach to combine GPW data with the Global Human Settlement Layer (GHS-BUILT). The GHS-BUILT Layer built-up grids are produced from Landsat imagery collections and reack back to the year 1975. The underlying GHSL technology analyzes satellite imagery to quantify the density and the location of build-up structures, which are interpreted as a "built-up presence index" (Pesaresi et al., 2015). In sparsely populated areas, both datasets underestimate population numbers in some cases. As these areas mostly differ between the datasets, we combine the information of both sources to minimize this type of measurement error.

Luminosity Data: We collect data from the US National Oceanic and Atmospheric Administration (NOAA) to measure luminosity at the grid cell level (NCEI, 2018a,b). Launched during the 1960s by the United States Department of Defense, the Defense Meteorological Satellite Program (DMSP) monitors meteorological, oceanographic, and solar-terrestrial physics on the globe. The Operational Linescan System (OLS) takes photos of the earth at night between 8:30 and 9:30 p.m. local time. While its main purpose today is the observation of clouds illuminated by moonlight, the data can also be used to detect light sources on earth. This raw data is the basis for NOAA's Version 4 DMSP-OLS Night Time Lights Time Series, which contains three different versions of nighttime lights data: cloud-free, raw and so-called "stable lights". Our analysis is based on the stable lights version, which is pre-processed by NOAA to remove sources of light that do not originate by human activities (e.g. lights from fires, sunlit and moonlit data, glare, lighting features from the aurora in the northern hemisphere). The data is available in a spatial resolution of 30 arc seconds and is coded in digital numbers (DN) ranging from 0 (implying there is no light in the corresponding area) to a maximum of 63.

2.3 Construction of ethnic inequality measures

2.3.1 Gini indices of ethnic inequality

Based on the geocoded data series, we calculate nighttime lights per capita for each ethnic homeland mapped in GREG. We repeat this procedure for each year between 1992–2013. Finally, we compute Gini indices of inequality in per capita luminosity across ethnic homelands via (country and time indices dropped)

$$\text{Gini}^{\text{e}} = \frac{1}{n}\left(n + 1 - 2\frac{\sum_{e=1}^{n}(n+1-e)l_e}{\sum_{e=1}^{n} l_e}\right), \tag{1}$$

where n is the number of ethnic groups in a given country and l_e is per capita GDP in the homeland of ethnic group e, proxied with luminosity per capita $\mathcal{L}_e$. Our approach allows us to compute ethnic inequality measures for 189 countries for the period 1992–2013. We use Equation (1) to compute two versions of ethnic inequality. The first version, Gini(NW), is methodologically similar to the original AMP approach and yields a non-weighted Gini index of ethnic inequality. For our second version, Gini(W), we add populations weights to Equation (1) to account for the size of ethnic groups.

Population-weighting of ethnic inequality: For some research questions, the theoretical underpinning requires having population-weighted measures of ethnic inequality. The non-weighted version, Gini(NW), takes ethnic groups as the unit of observation, and thus compares, as it were, representative individuals from all ethnicities in a country. A decrease in Gini(NW) thus reflects convergence in terms of average group incomes. The weighted version, Gini(W), reflects ethnic inequality when relative group sizes are taken into account. Gini(W) is better suited when the emphasis of the analysis is on group size as a proxy for relevance. Whether the size of an ethnic group reflects its economic and political power, however, may rely on the particular context.[2]

Ethnic inequality on the sub-national level: We also compute measures of ethnic inequality on the sub-national level. To this end, we use maps that identify first-level administrative (ADM1) areas from the GADM database of Global Administrative Areas (GADM, 2018). We construct sub-national versions of ethnic inequality by using ADM1 regions as underlying units of Equation (1). The GADM data contains information on 386,735 administrative areas on the globe. There are 3,609 first-level administrative divisions on the globe (usually "states" or "provinces").[3] Sub-national ethnic inequality measures can be computed for the period from 1992 to 2013, resulting in 66,912 region-year observations.

2.3.2 Calibrating the raw nighttime light data (making NTL more comparable across time)

The Defense Meteorological Satellite Program (DMSP) was launched during the 1960s to relay important weather and climate data to the military for more effective operations. Declassified in 1972 and handed to the National Oceanic and Atmospheric Administration (NOAA) in 1998, the program used 1970s technology for their satellites until the termination of the system in 2013. In the end, the program was never designed to obtain fine-grained estimates of comparative economic development. As a consequence, the accuracy of the nighttime light data

[2] Gini(W) assumes that the within-group distribution is perfectly flat: all members of an ethnic group receive the same average income. If we would relax this last restriction and allow for within-group disparities in income, we would end up at the traditional interpersonal Gini index of income inequality.

[3] The ADM1 sub-level of GADM resembles the NUTS-1 level of the EU's regional classification.

collected by the DMSP-OLS is strongly limited by the lack of on-board calibration, varied atmospheric conditions, satellite shift or sensor degradation. A further hurdle to comparability is that photographs of the earth were taken by six satellites between 1992–2013 (see Table C-1 in the appendix for a time-line), each degenerating at different rates and each providing much broader photographs when replacing their degenerated successors.

Missing calibration is less problematic for cross-country analyses at a given point in time, but temporal-inconsistency poses an essential problem when the goal is to construct comparable measures for a broad sample of countries observed over several years. Some empirical studies claim to resolve the time-inconsistency by using dummy variables for years. The implicit assumption of this strategy is that calibration-related problems affect luminosity synchronously. This assumption is, however, violated because ill-calibration is distributed asynchronously across regions, even within countries.[4] Some geographical studies address the problem of missing calibration, but these studies primarily focus on regional and national scales, while attempts to calibrate nighttime lights at a global coverage have been sparse for a long time. The geographical foundations for NTL calibration at a global scale have been developed only recently. We follow the novel approach of Li and Zhou (2017) to stepwise calibrate the DMSP-OLS data and to compute temporally consistent nighttime light time series. The approach builds on the IRQR method of Elvidge et al. (2009) and identifies a reference region that is as invariant as possible in terms of socioeconomic activity during the period 1992-2013. The technique uses an image of this region with maximum luminance as an anchor for inter-annual calibration (usually satellite-year F12-1999). The stepwise method of Li and Zhou (2017) accounts for several problems accompanying the original IRQR technique (a detailed description of the calibration approach is provided in Appendix A.1.).[5]

2.3.3 Removing the top-coding of nighttime lights (making NTL more comparable across space)

A related problem of the DMSP-OLS' vintage technology is that lights are top-coded at a maximum digital number of 63. This luminosity level is reached by many urban areas in both developing and advanced economies. For instance, using the raw light data implies that Abidja (Cote d'Ivoire), Acca (Ghana), Porto Novo (Benin), Manaus (Brazil), and Arequipa (Peru) are equally bright as Paris, London or New York. In total, top-coding affects between 3-5% of all lit pixels, but the scale of truncation is substantial, given that officially reported GDP per city in New York is more than 100 times higher than in Abidja. It also (falsely) suggests that the center and the outskirts of large cities are equally bright. Top-coding in the raw NTL time series implies that the obtained Gini-coefficients are downward biased in the majority of cases, as is cuts the upper end of the spatial income distribution. Moreover, rising inequality cannot

[4] A prime example of the asynchronous effect of calibration-related problems is Uzbekistan, where the post-calibration increase in luminosity is 7.12% in the region of Uzbeks and Russians, while it is 56.14% in the homeland of the Tatars. This is remarkable, given that Uzbekistan only covers an area of 448,978 square kilometers, and the distance between the homelands is minor. We observe similar asynchronous effects in many other countries.

[5] Well-known problems related to the original IRQR technique include, for instance, the sensitivity of the selected reference image and the reduction in the range of measured nighttime lights that results from the fact that only one image is used to calibrate the time series.

be illustrated properly in case that top-coded regions become wealthier.

Some studies have used "radiance-calibrated" lights to circumvent the problem of top-coding (e.g. Henderson et al., 2018).[6] While the method allows to construct data series without binding upper bounds, the resulting data is not comparable across time (Uprety et al., 2017). Instead, we use a Pareto distribution to model and correct top lights following Bluhm and Krause (2022). Specifically, we compute top-coding corrected mean luminosity $\mathcal{L}_i$ of the homeland of ethnic group i via the weighted average of the non-top-coded pixels λ_N and the top-coded pixels λ_T, i.e.

$$\mathcal{L}_i = \omega_{iN}\lambda_{iN} + \omega_{iT}\lambda_{iT} = \omega_{iN}\lambda_{iN} + (1 - \omega_{iN})\frac{\alpha}{\alpha - 1}\Phi_i, \tag{2}$$

where ω_{iN} and $\omega_{iT} = \omega_{iN}$ denote the shares of pixels below and above the threshold Φ_i of the Pareto distribution of top lights with shape parameter $\alpha > 0$.[7] We follow Bluhm and Krause (2022) by setting $\Phi_i = 55$ to ensure enough variation at the very top without affecting too much pixels.[8]

2.4 Examples and illustrations

In this section, we demonstrate that adjusted NTL series provide better proxies for economic development on the global level (Example I), and on the local level for ethnic homelands (Example II).

2.4.1 Example I: The effect of calibration and top-coding

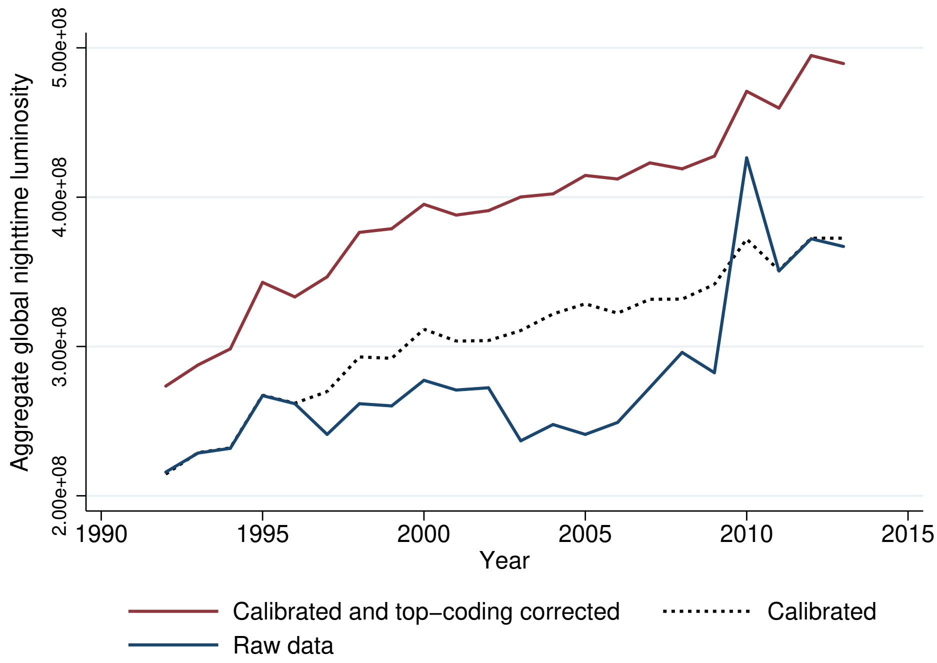
In Figure (1), we compare the development of world luminosity measured by the raw NTL data from DMSP-OLS (blue line) with our inter-annually calibrated series (black line) and with series that correct for ill-calibration and top-coding (red line). The figure reveals three implausibilities of the raw data: (i) the original DMSP-OLS series does not indicate a noteworthy increase in world luminosity between 1992 and 2005, while world GDP during this period increased by 48.5%. (ii) The time series reaches an unrealistically high peak in 2010, which is corrected in 2011. This peak is caused by the extreme overestimation of satellite-year F18-2010 and the satellite's lack of on-board calibration. (iii) The raw NTL data underestimates long-run growth trends in world GDP. We argue that this underestimation is not caused by the limited ability of nighttime lights to proxy economic development, but rather by the failure of the raw stable lights series to measure the "true" world luminosity. After calibrating the data, the development of NTL becomes more plausible and is much closer related to economic development. The data now reveals a rise in NTL between 1992 and 2005, the peak in 2010 is flattened, and the levels as well as the growth rate of NTL increase. The adjustments also yields a much greater accuracy

[6]This method uses DMSP-OLS VIS band in different fixed-gain levels (low, middle, high), where the fixed-gain setting allows to calculate the radiance based on pre-flight sensor calibration. Combining the gain modes expands the dynamic range of the final composite (Hsu et al., 2015).

[7]Bluhm and Krause (2022) provide many empirical tests about the size of the parameter α and show that a good rule-of-thumb is $\alpha = 1.5$.

[8]We examined the sensitivity to changes of the cut-off, and find that results are robust to reasonable changes of our threshold.

Figure 1 WORLD LUMINOSITY, RAW NIGHTTIME LIGHTS SERIES AND ADJUSTED SERIES



Notes: The figure shows the development of world luminosity over time, comparing the original raw nighttime lights series as reported by the Defense Meteorological Satellite Program's Operational Linescan System (DMSP-OLS) (labeled "raw data") with calibrated time series (labeled "Calibrated") and calibrated and top-coding corrected series (labeled "Calibrated and top-coding corrected"). The figure plots the yearly global averages of nighttime luminosity as implied by the three series. The processes to calibrate time series and to remove top-coding are described in detail in sections (2.3.2) and (2.3.3).

in terms of GDP measurement, increasing the correlation of the NTL series with GDP from 76.19% to 94.41%.

2.4.2 Example II: Ethnic inequality in Peru, Mali, and Tajikistan

Next, we demonstrate that the adjustment of NTL also yields more accurate development indicators on the local level. Peru, Mali, and Tajikistan offer expository examples from three continents (Figure 2.4). Similar consequences can be seen for many countries in our dataset. The intensity of the blue color scheme in panel (a) reflects the brightness of the raw observable light in ethnic homelands, averaged over all grid cells located in the homeland. Panels (b) and (c) show the percentage change in luminosity when we calibrate the NTL series and remove the top-coding.[9]

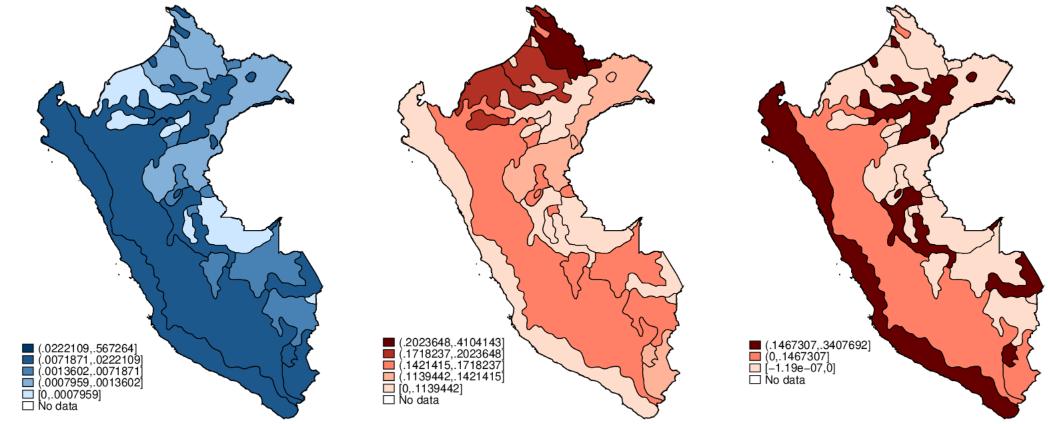
In the case of Peru, two main changes are observable. First, calibration of the data leads to higher mean incomes in the homeland of the Coreguaje and Sioni. Second, mean incomes in the coastal regions and around the Lake Titicaca increase when we remove top-coding. This increase is plausible, because the regions are home to the most prosperous cities of Peru, including Lima,

[9]The illustrated classes are recovered from the individual national distributions.

Figure 2 EXAMPLE: ETHNIC INEQUALITY IN PERU, MALI, AND TAJIKISTAN

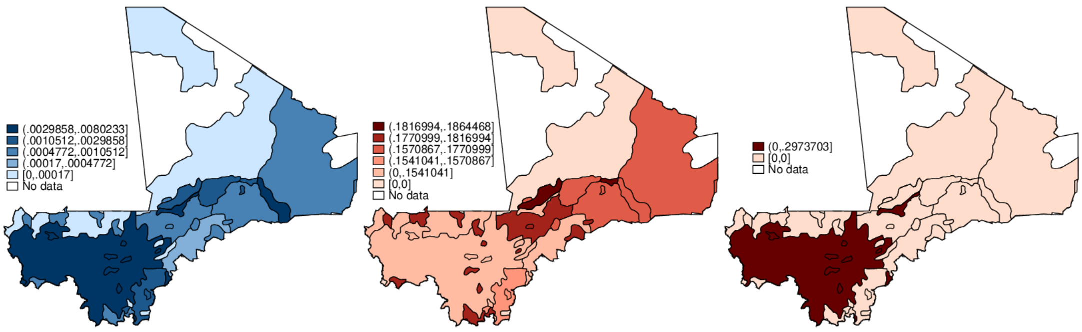
(I) Peru

(a) Raw luminosity data (b) Calibration effect (change %) (c) Top-coding effect (change %)



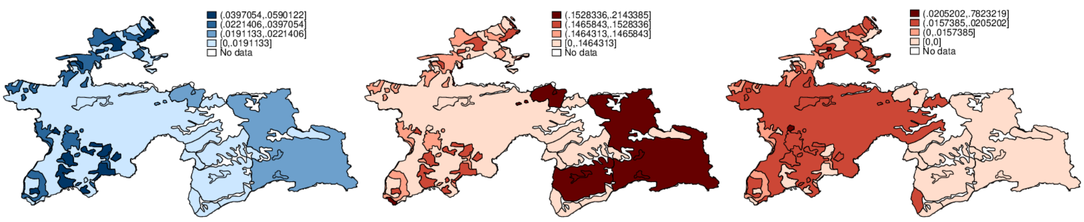
(II) Mali

(a) Raw luminosity data (b) Calibration effect (change %) (c) Top-coding effect (change %)



(III) Tajikistan

(a) Raw luminosity data (b) Calibration effect (change %) (c) Top-coding effect (change %)



Notes: The maps shows how the calibration of the raw nighttime light series provided by the Defense Meteorological Satellite Program's Operational Linescan System (DMSP-OLS) and the removal of top-coding influences the estimated income level of ethnic homelands. The panel on the left-hand side shows estimates for group-level incomes obtained by the the original raw nighttime lights series (Panel a, blue color). The panels in the middle and the right-hand side demonstrate the percentage change in mean per capita luminosity when we calibrate (Panel b) the data and remove the top-coding truncation (Panel c). The processes to calibrate time series and to remove top-coding are described in detail in sections (2.3.2) and (2.3.3). Peru, Mali and Tajikistan serves as expository examples from three continents with high levels of ethic inequality.

Arequipa, Trujillo and Chiclayo at the coastal region, and Puno and Juliaca at the shore of the Lake Titicaca.

There is large heterogeneity in how correcting nighttime lights influences measures of ethnic inequality. For Peru, the change in the non-weighted Gini index is minor. The Coreguaje and Sioni are among the poorest ethnic groups in Peru, whereas the cities at the coast and at the Lake Titicaca are among the richest regions in the country. The income increase of the poorer regions is neutralized by the income increase of the richer regions, and the Gini remains stable around a very high level (changing from 0.722 to 0.732). Much of the ethnic inequality in Peru results from low minority incomes. The richest (Brazilians) and the two poorest (Cocamas and Chane) of the 14 ethnic groups in Peru make up only 0.1% of the population (approximately 22,000 people). Weighted inequality is therefore significantly lower than non-weighted inequality. Also, the effects of light data adjustment are much stronger for weighted inequality. Since the coastal region and Puno are not only among the richest but also the among most populous regions, raising their average income by adjusting NTL increases the weighted Gini by 36.4%, from 0.110 to 0.150.

In Mali, most ethnic groups are affected by calibration, while top-coding only changes the mean income in the homeland of the Mandingo, where the capital Bamako is located. These changes compress the income distribution and lead to a decline in Gini(NW) of about 2 Gini-points (from 0.640 to 0.620). Again, the effects are different for Gini(W). Given that the Mandigo are one of the larger groups of the Malinese population, raising their mean income by almost 30% through the elimination of top-coding leads to an increase in weighted inequality by 11%, from 0.282 to 0.310.

Adjusting the nighttime lights also has heterogeneous effects on computed ethnic inequality in Tajikistan. While non-weighted inequality remains stable (changing from 0.614 to 0.613), we observe a sizable decrease in weighted inequality from 0.813 to 0.770.

Key conclusions from our examples: Taken together, our examples demonstrate that compared to raw NTL series, adjusted nighttime lights are better suited to approximate economic development on both the global and the local level. Our local analysis also illustrates that calibration and top-coding adjustment leads to asynchronous changes in implied wealthiness of ethnic homelands. In a similar vein, the effect on ethnic inequality varies across countries and among both weighted and non-weighted inequality measures. An important conclusion from these examples is that ill-calibration and truncation has asynchronous effects across space. Similar asynchronous changes are observable also across time (see Figure B-1 in the appendix). Hence, when the goal is to construct longitudinal measures based on geospatial variation in NTL, using the raw NTL results in substantial biases. Because of their asynchronous nature, biases from imprecise approximations of per capita GDP for ethnic homelands cannot be mitigated in empirical estimations by simply adding country and year fixed effects.

Influence of NTL series on measurements of ethnic inequality: Replacing raw NTL series by adjusted NTL series leads to a substantial change in the measured levels of ethnic inequality (for details, see Appendix A.2). In general, using non-adjusted luminosity tends to inflate ethnic inequality measures. However, the change in ethnic inequality is asynchronous and depends on specific country characteristics.

2.5 Ethnic inequality in the world

Figures (3a) and (3b) show the distribution of ethnic inequality across the globe. The figures refer to the most recent numbers of ethnic inequality from the year 2013 (Tables C-2 and C-3 in the appendix list the exact Gini indices and the number of groups per country).

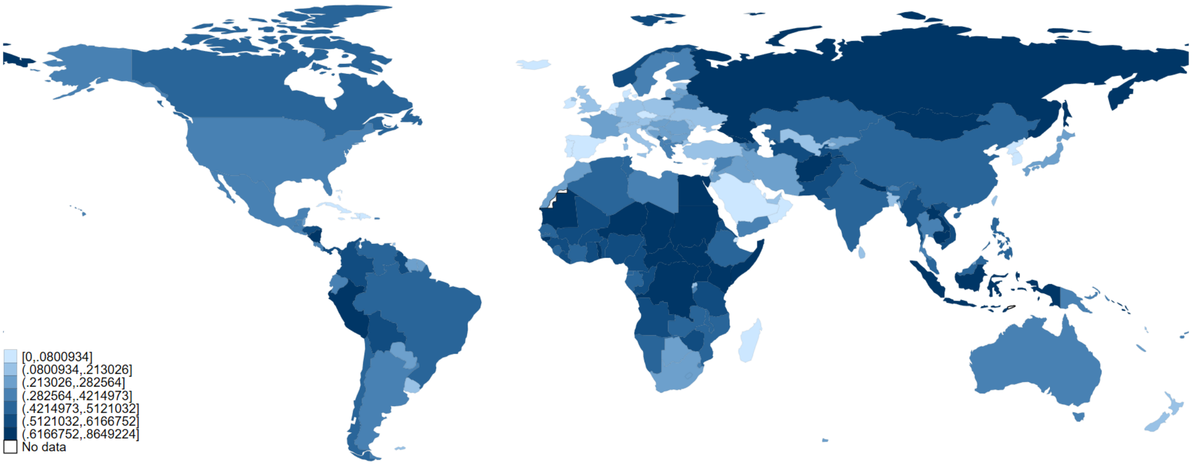
Four observations are particularly noteworthy. First, population-weighted ethnic inequality is, on average, lower (0.103) than inequality between representative group members (0.316). The most extreme differentials between non-weighted and weighted inequality are Tunisia (moving from 0.510 to 0.008), Finland (0.386 to 0.024) and Nicaragua (0.639 to 0.018). Second, there are distinct regional patterns in ethnic inequality. While between-group inequality is high in almost all countries in Africa, Asia and South America, interethnic income differentials are less pronounced in Europe, Arabia, and the Caribbean. These regional patterns are similar for both versions of ethnic inequality. Third, inequality across ethnic homelands (0.316) is, on average, slightly smaller than inequality of household-level disposable incomes (0.38). However, the standard deviation of ethnic inequality (0.24) is higher than that of overall inequality (0.08), suggesting that countries are more heterogeneous in terms of ethnic inequality than in terms of household inequality (see Figure B-2 in the appendix for a detailed comparison). Fourth, there are 38 countries with only a single ethnic group, resulting in a Gini index of 0.

Our panel dataset also allows to track changes in ethnic inequality across time. Figure (4) shows that ethnic inequality has declined between 1992 and 2013. Despite the level differences, the trend in ethnic inequality is comparable between Gini(NW) and Gini(W). The decline in weighted inequality (21.1%, from 0.131 to 0.103 Gini points) is slightly larger than the decline in non-weighted inequality (16.8%, from 0.394 to 0.316 Gini points). The dynamics in ethnic inequality differ substantially across geographic regions (see Figures B-5 and B-6 in the appendix). While ethnic inequality decreased in Latin America, Asia and large parts of Africa, it stagnated in North America and Europe, and increased in Arabia.

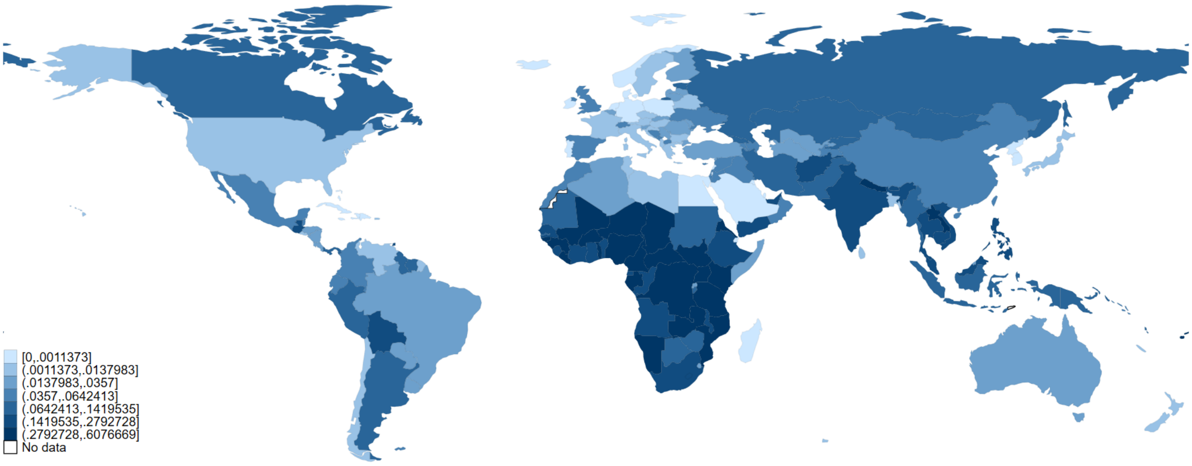
In Figure (B-3) in the appendix, we present estimates of ethnic inequality on the sub-national level. Similar to the country-level data, we observe regional patterns also with respect to ethnic inequality in ADM1 regions. Resembling the trends on the national level, we observe a decrease in sub-national ethnic inequality between the early 1990s and 2013. Between-group income differentials are, however, more persistent on the sub-national level than on the country-level.

Unconditional correlation of ethnic inequality and economic development: Figure (B-4) in the appendix shows the unconditional correlation between ethnic inequality and economic development, measured in the log of real per capita GDP. For both versions of ethnic inequality, we observe a strong negative correlation with economic development. The correlation is -53.3% for non-weighted ethnic inequality and -58.4% for population-weighted ethnic inequality.

Figure 3 GINI INDICES OF ETHNIC INEQUALITY IN THE WORLD, 2013



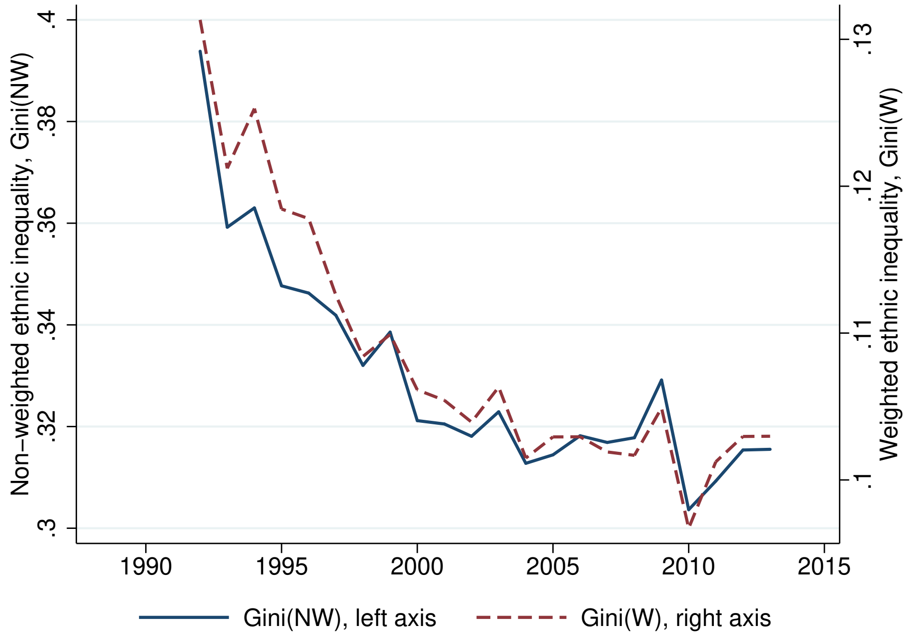
(a) Non-weighted Gini index of ethnic inequality



(b) Population-weighted Gini index of ethnic inequality

Notes: The figure shows the global distribution of our non-weighted measure of ethnic inequality (Gini(NW), Panel a) and or population-weighted measure of ethnic inequality (GINI(W), Panel b) for the most recent year in our sample (the year 2013). The population-weighted version weights the mean income level of ethnicities by their relative size. The construction process of both measures for ethnic inequality measures is described in detail in Section (2.3). The selection of classes used for the visualization refers to the empirical quantiles of the distribution of the ethnic inequality measures in the year 2013.

Figure 4 DEVELOPMENT OF GLOBAL ETHNIC INEQUALITY OVER TIME, 1992–2013



Notes: The figure shows the development of ethnic inequality (world average), measured by the non-weighted (blue line, axis on the left-hand side) and population-weighted (red line, axis on the right-hand side) Gini index. Due to data availability of nighttime lights measured by the DMSP-OLS satellites, our indices cover the period 1992–2013. The construction process of both measures for ethnic inequality measures is described in detail in Section (2.3).

3 Ethnic inequality and comparative economic development

3.1 Cross-sectional results

We start our analysis on the role of ethnic inequality for comparative economic development by replicating the Alesina et al. (2016) cross-sectional regression

$$y_{i,2000} = \beta \text{Gini}^{e}_{i,2000} + \mathbf{X}_{i,2000}\boldsymbol{\lambda} + \delta_r + \varepsilon_{i,2000} \tag{3}$$

where $y_{i,2000}$ is the log of real per capita GDP in country i observed in the year 2000, and $\text{Gini}^{e}_{i,2000}$ is a measure of ethnic inequality. To exactly replicate the results of Alesina et al. (2016) and leave the measure of ethnic inequality as the only degree of freedom, we use $y_{i,2000}$ as provided in their replication files. We compare the effects of three different variants of ethnic inequality measures: (i) the original measure developed by Alesina et al. (2016), (ii) our non-weighted measure Gini(NW) that uses corrected light data and (iii) our weighted version Gini(W) that uses corrected light data and accounts for the size of ethnic groups.

Table (1) reports the empirical results for four specifications. Column (1) presents results of a parsimonious model on the relationship between ethnic inequality and the log of per capita GDP. Column (2) augments the empirical model by a set of fixed effects for supranational regions, δ_r,

Table 1 ETHNIC INEQUALITY AND COMPARATIVE ECONOMIC DEVELOPMENT—CROSS-SECTIONAL ESTIMATES

Dependent variable: Real per capita GDP, log(GDP^{pc})				
	Parsimonious (1)	Regional Effects (2)	Spatial Inequality (3)	More Controls (4)
	Panel A: Original Gini index by Alesina et al. (2016)			
Ethnic inequality	-2.568***	-1.391***	-1.390***	-1.117**
	(0.340)	(0.259)	(0.342)	(0.549)
Observations (# countries)	173	173	173	173
R-Squared	0.242	0.670	0.670	0.689
Fixed effects (regions)	No	Yes	Yes	Yes
Spatial inequality	No	No	Yes	Yes
Full set of controls	No	No	No	Yes
	Panel B: Non-weighted Gini index with corrected NTL, Gini(NW)			
Ethnic inequality	-3.269***	-1.847***	-1.954***	-2.037***
	(0.326)	(0.279)	(0.371)	(0.506)
Observations (# countries)	173	173	173	173
R-Squared	0.319	0.375	0.702	0.703
Fixed effects (regions)	No	Yes	Yes	Yes
Spatial inequality	No	No	Yes	Yes
Full set of controls	No	No	No	Yes
	Panel C: Weighted Gini index with corrected NTL, Gini(W)			
Ethnic inequality	-5.328***	-2.057***	-1.485**	-1.379**
	(0.505)	(0.669)	(0.672)	(0.656)
Observations (# countries)	173	173	173	173
R-Squared	0.356	0.638	0.654	0.680
Fixed effects (regions)	No	Yes	Yes	Yes
Spatial inequality	No	No	Yes	Yes
Full set of controls	No	No	No	Yes

Notes: The table reports our baseline regressin results on the relationship between ethnic inequality and the log of real per capita GDP for the year 2000. Robust (heteroskedasticity—adjusted) standard errors are reported in parentheses. The dependent variable is the log of real per capita GDP, measured using data from the Penn World Tables Version 9.1. Ethnic inequality is measured as described in Section (2) using differences in nightime lights across ethnic homelands. The three ethnic inequality measures used in the table are: ethnic inequality as taken from Alesina et al. (2016) (Panel A); our non-weighted version of ethnic inequality using corrected light data (Panel B) and our weighted version of ethnic inequality using corrected light data and weights for the size of ethnic groups (Panel C). The table reports results for four different specifications: The parsimonious model (Column 1) is step-wise augmented by fixed effects for geographic regions (using the classification of the World Bank, Column 2), a measure of spatial inequality (Column 3), and the full set of control variable used in the baseline table by Alesina et al. (2016) (Table 2). These variables include: spatial inequality (Gini measure), the log number of ethnicities, ethnic inequality in the population (Gini measure), ethnic inequality in size (Gini measure; based on area), the log of land area, and the log of the population in the year 2000.

*** Significant at the 1 percent level,
** Significant at the 5 percent level,
* Significant at the 10 percent level

to account for cross-regional heterogeneity in unobserved factors as well as regional differences in ethnic inequality and comparative economic development. In Columns (3)-(4), we account for additional control variables included in the matrix $\mathbf{X}_{i,2000}$. Column (3) adds a spatial inequality, Column (4) presents results for the full set of control variables used for the baseline results of Alesina et al. (2016).[10]

In all model specifications, ethnic inequality is negatively associated with the log of real per capita GDP. The estimated coefficient on ethnic inequality is statistically significant at the 1% level in all models. However, we observe a sizable increase in the estimated parameters when we replace the original Gini index developed by Alesina et al. (2016), shown in Panel A, with our comparable non-weighted measure that we construct using corrected nighttime lights (Panel B). Accounting for standard deviations of the variables, the differences suggests that using corrected nighttime lights leads to an increase in the coefficient on ethnic inequality by about 20%. These differences persist when we use our Gini index of population-weighted ethnic inequality (Panel C).

Our cross-sectional results deliver two main results. First, the economically and statistically sizable relationship between ethnic inequality and comparative economic development found by Alesina et al. (2016) re-appears when ethnic inequality is measured based on corrected nighttime lights. Second, the size of the coefficient on ethnic inequality increases considerably when ethnic inequality is measured based on corrected light data.

3.2 Panel data results

The static cross-sectional model provides no conclusions about the contribution of ethnic inequality to contemporary economic growth. From a policy perspective, however, it is important to understand whether the relationship between ethnic inequality and per capita GDP is historically grown or whether it reflects a negative effect of between-group inequality on modern economic growth. On the one hand, the relationship between ethnic inequality and per capita GDP could be driven by historical factors whose importance declined with the transition to modernity, such that the strong association between ethnic inequality and per capita GDP mainly is inherited from developments in the distant past. On the other hand, the relationship might have been strengthening over time, such that ethnic inequality would continue to affect countries' growth rates. In recent years, ethnic inequality has not only been related to conflict (see e.g. Østby, 2008, Cederman et al., 2011, Cederman et al., 2015, Huber and Mayoral, 2019), but also to lower levels of trust (Hodler et al., 2020), and to governance related factors (Baldwin and Huber, 2010, Huber and Suryanarayan, 2016, Kyriacou, 2013). As these factors are important determinants of economic growth themselves, an ongoing negative effect from ethnic inequality on growth seems plausible. In the following chapter, we exploit our novel dataset on ethnic inequality in a dynamic panel data model of GDP to explore such a potential relationship.

The most important feature of our longitudinal data set is that it allows us to estimate dynamic models that eliminate time-invariant heterogeneity in the form of historical, institutional,

[10] These variables include spatial inequality, the log number of ethnic groups, measures for ethnic inequality in the population and in land area that capture inequality in the population of ethnic groups and the size of ethnic homelands, as well as measures for the size of countries (the log of total land area and the log of the population in the year 2000).

geographic, and cultural characteristics by including country fixed effects. Country-level fixed effects also account for any time-invariant unobservables that are simultaneously correlated with ethnic inequality and economic growth. The panel structure also allows us to address three additional econometric challenges: (i) ethnic inequality may impact GDP differently over time, particularly given that ethnic inequality has decreased since the early 1990s (Figure 4). (ii) the estimated parameter of ethnic inequality at a specific point in time may be influenced by period-specific events. (iii) GDP may be influenced by cross-national shocks and trends over time.

We address these challenges by estimating a full dynamic panel data model of GDP

$$y_{it} = \beta \text{Gini}^e_{it} + \sum_{j=1}^{\phi} \omega_j y_{it-j} + \eta_i + \zeta_t + \varepsilon_{it}, \tag{4}$$

where we include country-fixed effects η_i to account for time-invariant cross-country heterogeneity and fixed period effects ζ_t to address period-specific shocks and trends. We follow Acemoglu et al. (2019) and include four lags of GDP to account for path dependency and GDP dynamics. Modeling GDP dynamics also allows us to account for a potential correlation between ethnic inequality and lagged levels of per capita GDP and eliminates the potential of a spurious correlation caused by non-stationary time-series.[11] Including GDP dynamics in our panel setting is also important to fulfill the standard sequential exogeneity assumption in linear dynamic panel data models. [12]

In Section (2.5), we document large and persistent differences in the level of ethnic inequality across geographic regions. Our descriptive statistics also show that there are dynamics in ethnic inequality over time and that these dynamics differ across continents (see Figures B-5 and B-6). To rule out that our results are driven by heterogeneous trends, we also estimate augmented versions of Equation (4) where we include country-specific trends (π_{it}) and account for time-varying unobservables on the continent-level by including fixed effects for continent-years ($\nu_c \times \mu_t$)

$$y_{it} = \beta \text{Gini}^e_{it} + \sum_{j=1}^{\phi} \omega_j y_{it-j} + \eta_i + \zeta_t + \nu_c \times \mu_t + \pi_{it} + \varepsilon_{it}. \tag{5}$$

Table (2) reports the results of our dynamic panel data estimations. The main result is that there is a negative and statistically significant relationship between ethnic inequality and modern economic growth. Columns (1)–(3) present results for the non-weighted version of our Gini index of ethnic inequality, columns (4)–(6) shows the results for our weighted variant. For both versions, we present estimates of our baseline model of Equation (4) and successively include continent-year fixed effects and country-specific time trends (Equation 5).

[11] Hamilton (2018) demonstrates that the residuals ε_t of a regression $x_t = \beta_0 + \sum_j^J = 1\beta_j x_{t-j} + \varepsilon_t$, $j = 1, \ldots, J$ are stationary with very high probability for $J = 4$.

[12] Strict exogeneity is violated when the model includes lagged dependent variables. With lagged dependent variables, β is identified when *sequential exogeneity* is fulfilled, i.e.

$$\mathbb{E}(\varepsilon_{st} | y_{st-1}, \ldots, y_{st_0}, \text{Gini}^e_{st}, \ldots, \text{Gini}^e_{st_0}, \eta_i, \zeta_t) = 0$$

for all $y_{st-1}, \ldots, y_{st_0}, \text{Gini}^e_{st}, \ldots, \text{Gini}^e_{st_0}, \eta_i$, and ζ_t, and for all s and $t \geq t_0$. This, however, is the case only when GDP dynamics are sufficiently specified.

Table 2 ETHNIC INEQUALITY AND ECONOMIC GROWTH—DYNAMIC PANEL DATA ESTIMATES, 1992–2012

Dependent variable: Real per capita GDP, log(GDP^{pc})

	Non-weighted Ethnic inequality Gini(NW)			**Weighted Ethnic inequality Gini(W)**		
	Baseline (1)	Continents (2)	Trends (3)	Baseline (4)	Continents (5)	Trends (6)
Ethnic inequality	-0.096***	-0.096***	-0.096***	-0.175**	-0.177***	-0.177***
	(0.0273)	(0.0277)	(0.0278)	(0.0681)	(0.0680)	(0.0681)
log(GDP^{pc})$(t-1)$	1.109***	1.104***	1.104***	1.104***	1.099***	1.099***
	(0.0513)	(0.0497)	(0.0497)	(0.0516)	(0.0498)	(0.0498)
log(GDP^{pc})$(t-2)$	-0.156***	-0.151***	-0.151***	-0.154***	-0.148***	-0.148***
	(0.0373)	(0.0375)	(0.0376)	(0.0371)	(0.0373)	(0.0373)
log(GDP^{pc})$(t-3)$	0.0292	0.0262	0.0261	0.0305	0.0275	0.0274
	(0.0546)	(0.0541)	(0.0541)	(0.0546)	(0.0542)	(0.0542)
log(GDP^{pc})$(t-4)$	-0.0920***	-0.0880***	-0.0879***	-0.0948***	-0.0914***	-0.0913***
	(0.0184)	(0.0180)	(0.0180)	(0.0188)	(0.0187)	(0.0187)
Observations	3615	3615	3615	3615	3615	3615
Countries	167	167	167	167	167	167
R-Squared	0.954	0.956	0.956	0.954	0.956	0.956
F Stat	2705.9	655.6	649.5	2714.2	657.6	651.5
Country Fixed Effects	yes	yes	yes	yes	yes	yes
Period Fixed Effects	yes	yes	yes	yes	yes	yes
C × Y Fixed Effects	no	yes	yes	no	yes	yes
Trend (country-specific)	no	no	yes	no	no	yes

Notes: Cluster robust standard errors are reported in parentheses. The dependent variable is the log of real per capita GDP, measured using data from the Penn World Tables Version 9.1. Ethnic inequality is measured as described in Section (2) using differences in nightime lights across ethnic homelands. The ethnic inequality measures used in the table are: our version of ethnic inequality using corrected light data (columns 1–3) and our version of ethnic inequality using corrected light data and weights for the size of ethnic groups (columns 4–6). All specifications include country fixed effects and year fixed effects. The columns labeled "Baseline" report parameter estimates for models where the log of real per capita GDP is regressed on ethnic inequality, controlling for GDP dynamics, fixed effects for countries and fixed effects for years. Model "Continents" additionally includes Continent×Year (C × Y) fixed effects, model "Trends" adds country-specific trends.

*** Significant at the 1 percent level,
** Significant at the 5 percent level,
* Significant at the 10 percent level

Our benchmark parameter estimate in column (1) is -0.096, suggesting that a one-standard-deviation increase in ethnic inequality ($\Delta\text{Gini}^e = 0.256$) is associated with a 2.4% decline in real per capita GDP. The parameter estimate is statistically significant at the 1% level. Inferences do not change when we account for time-varying unobservables on the continent level and country-specific time trends. The results are also similar if we employ our weighted version of ethnic inequality, both in terms of economic and in terms of statistical significance. The marginal effect of a one-standard-deviation change is slightly larger when we consider population weighted ethnic inequality (2.5%).

The cumulative long-run effect of a permanent transition from an equal distribution of incomes across groups to a situation where all wealth is concentrated at a single group can be computed using the estimated GDP dynamics via

$$\frac{\hat{\beta}}{1 - \sum_{j=1}^{J} \hat{\omega}_j}. \tag{6}$$

The results suggest that over multiple periods, the cumulative long-run effect of ethnic inequality is -15.8% of real per capita GDP.

Our panel data estimates deliver two important pieces of information that cannot be obtained based on the static cross-sectional model. First, ethnic inequality continuous to be related to contemporary growth. Second, lagged levels of GDP eliminate the manifold historical roots of comparative economic development. Accounting for GDP dynamics hence rules out that the relationship between ethnic inequality and contemporary economic growth is primarily driven by historical factors.

3.3 Robustness

Critical threats to the validity of our results come from five sources: (i) the assumptions of our dynamic panel data model may be violated; (ii) the results may be driven by our construction process of ethnic inequality; (iii) the estimated relationship may be confounded by factors that simultaneously influence GDP and ethnic inequality; (iv) the estimated parameter of ethnic inequality may reflect the effect of spatial inequality or other aspects of the ethnic composition; and (v) there may be heterogeneity in the growth effect of ethnic inequality. We next examine these threats.

3.3.1 Alternative estimation strategies

For our benchmark estimates, we model GDP dynamics using four lags of GDP per capita, which is motivated by the recent literature on economic growth (e.g. Acemoglu et al., 2019) and time-series econometrics (e.g. Hamilton, 2018). Figure (B-7) in the appendix shows the parameter estimates and t-statistics when we use alternative specifications of GDP dynamics with a maximum of between 1 and 6 lags. The figure shows that different specifications of GDP dynamics have little impact on inferences.

The inclusion of GDP dynamics comes at the cost of a mechanical correlation between the lagged dependent variable and the error term, which causes an asymptotic bias of order $1/T$ (Nickell, 1981). Our model draws on data with a relatively long time horizon (1992 to 2013,

$N = 22$), alleviating concerns about a "Nickell-bias".[13] To further alleviate concerns about a dynamic panel bias, Table (C-4) in the appendix reports results from alternative estimation strategies that deal with the Nickell-bias. Columns (1)–(2) show our baseline estimates as benchmarks. Columns (3)–(4) report the results when we use a bias-corrected version of the LSDV estimator (Bruno, 2005a,b).[14] The results are very close to the baseline estimates, and the Wald test of equality of parameter estimates cannot be rejected ($p = 0.862$ for non-weighted ethnic inequality and $p = 0.798$ for weighted ethnic inequality).

Columns (7)–(8) provide accompanying results from GMM approaches. We consider moment conditions of the form (Arellano and Bond, 1991)

$$\mathrm{E}\left[(\varepsilon_{it} - \varepsilon_{it-1})(y_{is}, \mathrm{Gini}^{e}_{is+1})'\right] = 0 \ \forall \ s \leq t - 2 \tag{7}$$

that follow from the standard sequential exogeneity assumption of the dynamic panel setting. The resulting difference GMM estimator produces consistent estimates of the dynamic panel model for finite T given that there is no AR(2) serial correlation in the first-differenced residuals and that there is no asymptotic bias in the difference GMM estimates caused by a large number of instruments (for a brief description of these problems, see Roodman, 2009a,b; Alvarez and Arellano, 2013).[15] Qualitatively, the results are comparable to the outcomes of the previous columns, but the parameter estimates are larger when applying GMM methods. The statistical tests reported in the table show that the estimator satisfies the criteria necessary to obtain consistent results, most importantly absence of AR(2) correlation. A drawback of this estimator is that the number of moment conditions is of order T^2. The p-value of Hansen's J-test suggests that there is no problem of overfitting in our model, but we further alleviate concerns in this direction by presenting the results of the Han and Phillips (2010) method in columns (5)–(6). An advantageous feature of this estimator is that it imposes no restrictions on N and T other than the simple requirements $N \times T \to \infty$ and $T > 3$. Thus, Gaussian asymptotics hold irrespective of the composition of the sample. The outcomes are close to the difference GMM results, but somewhat larger in size.

Our dynamic panel data model assumes that the relationship between ethnic inequality and economic development is linear. To address concerns about a potential misspecification error, we run nonparametric regressions where we make no assumption about the functional form between ethnic inequality and economic growth. The construction of our nonparameteric estimator follows a two-step procedure. We first consider a general semiparametric version of our dynamic panel data model in which ethnic inequality enters as a nonparameterized function. We estimate the parameters of this model (see Baltagi and Lee, 2002 for the construction of

[13] The extent of bias can be estimated using the coefficients of the regression (see Nickell, 1981)

$$\mathrm{plim}_{N\to\infty}(\hat{\pi} - \pi) \simeq \frac{-(1 + \sum_j \pi)}{T - 1} = -0.090.$$

[14] The estimator approximates and eliminates the dynamic panel bias using an initially consistent estimator. Unlike other methods that make use of the Kiviet (1995) approach to estimate the bias in the small T context, the Bruno (2005a,b) estimator is also feasible for unbalanced panels. To implement the estimator, we use 100 bootstrapping iterations to obtain robust standard errors and use the Arellano and Bond (1991) method as initially consistent estimator.

[15] We collapse our instrument matrix to avoid a bias originating from "instrument proliferation".

consistent estimates), use the parameters to estimate the error component residual, and fit the nonparametric function by running local-constant kernel regressions of economic growth on ethnic inequality in the second step. A detailed description of our method is given in Appendix A.3. Columns (9)–(10) of Table (C-4) report average derivatives of per capita GDP with regard to ethnic inequality that can be interpreted as marginal effects. Standard errors are based on 100 bootstrapping iterations (Cattaneo and Jansson, 2018). The results are very similar to our baseline outcomes, establishing that our findings are not affected by functional misspecification.

3.3.2 Changes in the construction of ethnic inequality measures

The construction process of our ethnic inequality measures involved some crossroads where we needed to decide on which path to proceed. We next examine the consequences for the growth effect of ethnic inequality if we alter the assumptions underlying the construction of our Gini indices.

An important assumption of our Gini index refers to our handling of polygons that inhabit multiple ethnic groups: let n_p denote the number of ethnic groups in polygon p. In the majority of cases (7,383 polygons), there is only one ethnic group per homeland ($n_p = 1$), but we have multiple groups in 21% of the polygons ($n_p = 2$ for 1,586 polygons; $n_p = 3$ for 34 polygons). To ensure that our measure is based on the broadest possible geographic coverage, we approximate the population m_p^g of ethnic group g via $m_p^g = \frac{m_p}{n_p}$ if $n_p > 1$, and compute population shares via

$$\mu_p^g = \frac{m_p^g}{m}, \; m = \sum_{p \in T} m_p. \tag{8}$$

This rule potentially results in overestimation for very small g (De Luca et al., 2018). In Table (C-5), we investigate whether the results change when we exclude these small groups. There is no guidance from theory about the critical size below which groups are to be classified as "small". We hence compute three alternative measures of ethnic inequality where we exclude groups with a population size of 2,000 individuals or less (column 2) and those that account for a fraction of 0.1% (column 3) and 1% (column 4) of population. The resulting Gini indices deliver estimates that are very close to those of our preferred measure of ethnic inequality.

Another important assumption relates to the map of ethnic homelands that is used to construct ethnic inequality series. Each map has its individual advantages and disadvantages, and there is no strict dominance of one map over the others. A drawback of GREG is that migration flows during the past 50 years may have changed the ethnic composition and the relative importance of individual groups in some countries. Despite large inertia in ethnic settlement (Weidmann et al., 2010b), it is a concern that changes in ethnic homelands caused by migratory patterns may influence the measured level of ethnic inequality. To assess whether our results are biased by migration, we construct two alternative measures of ethnic inequality based on the GeoEPR 2018 mapping of Vogt et al. (2015). GeoEPR geocodes the homelands of ethnic groups based on very recent spatial distributions. The downside of this database is that it only covers "politically relevant ethnic groups". Our first GeoEPR-based variant of ethnic inequality includes all border changes noted in GeoEPR. For the second variant, we geocode the data backwards to match the fixed borders of the year 1969. The fixed 1969 borders enable a closer comparison with our baseline variant of ethnic inequality. For both border variants, we compute population-weighted and non-weighted versions of ethnic inequality. The results, reported in Table (C-6), show that using a different map of ethnic inequality has little impact on inferences. The Wald test also suggests that the parameter estimates are not significantly different from our baseline results.

A further concern about the construction of our ethnic inequality measure is that many ethnic groups co-exist in large urban areas, and that the assignment of cities to specific ethnic homelands may bias the measurement outcome. To alleviate these concerns, we compute alternative measures on ethnic inequality where we cut out all urban areas with more than 750,000 inhabitants from our maps (data on the spatial distribution of large cities is taken from Nordpil, 2018). This adjustment affects a total of 590 urban areas. Again, we compute population-weighted and non-weighted versions of ethnic inequality and examine the changes in the parameter estimates compared to our baseline Gini index (see Table (C-7) in the appendix). Excluding cities does not change inferences, and the parameter estimates are not statistically distinguishable from the baseline outcomes.

Taken together, our results show that altering important assumptions in the construction process of ethnic inequality has little impact on the strong negative association between ethnic inequality and economic development.

3.3.3 Confounding factors

Our baseline results may be confounded by factors that simultaneously influence ethnic inequality and economic development. Confounding can occur by factors that influence the measure of ethnic inequality and by variables that are economically related to ethnic inequality and to growth. With respect to the construction of ethnic inequality measures, a concern may be that our results are driven by the number of ethnic groups, an unequal clustering of population across ethnic homelands, or differences in the size of ethnic homelands. Two reasons give us confidence that this is not the case. First, the replication of the original Alesina et al. (2016) specifications, shown in Table (1) in the appendix, demonstrates that the negative association between ethnic inequality and economic development remains unaffected if we include the number of ethnic groups per country or Gini indices of population and land area that account for inequality in the size of homelands (Column IV). Second, the construction-related confounding factors are time-invariant and are hence absorbed by the fixed effect in our dynamic panel data estimates. With respect to economic confounders that are correlated with ethnic inequality and economic development, the answer is less clear and requires careful empirical investigation.

We augment our panel data model of Equation (4) by including covariates that are potentially related to both ethnic inequality and growth. Little is known about the entanglement of interethnic income inequality and standard growth factors. Our selection of potential confounders is therefore motivated by the literature on ethnic fractionalization and growth. We include human capital to account for the observation that ethnic discrimination lowers human capital acquisition (Tomaskovic-Devey and Johnson, 2005; Docquier and Rapoport, 2003) and control for net investment relative to GDP to address the argument that countries with higher ethnic fractionalization have lower investment rates (Mauro, 1995; Montalvo and Reynal-Querol, 2005b). Alesina and La Ferrara (2005) describe that higher ethnic diversity leads to an increasing tendency to split countries into smaller, more homogenous political entities and that secession is more likely to occur if countries engage in free trade, because trade decreases the "benefit of size". We account for this argument by including the KOF Globalization Index (Gygli et al., 2019). We also address the argument that fertility may be a strategic choice for ethnic groups engaged in redistribution conflict (Janus, 2013) and include the fertility rate in the list of controls. Finally, we include natural resource rents to account for the positive impact of natural resources on between-group conflict (Berman et al., 2017) and use coups d'états as measures for political instability caused by ethnic inequality (Houle and Bodea, 2017).

The results are reported in Tables (C-8) and (C-9) in the appendix. The inclusion of potential confounding factors has little impact on inferences. The parameter estimate of ethnic inequality retains its economical and statistical significance in each specification, regardless of whether we use our non-weighted or our population-weighted Gini index of ethnic inequality.

3.3.4 Spatial inequality and population-related inequality

Our measures of ethnic inequality essentially combine information on income inequality across regions with that of population size and ethnic diversity. A potential thread of this strategy is that the estimated parameter in our empirical model captures the effect of other dimensions of inequality, most importantly inequality between sub-national units ("spatial inequality") or inequality in terms of the size and ethnic composition of population ("ethnic fractionalization"). We now examine whether our parameter estimate survives a horse race with these factors.

In Table (C-10) in the appendix, we first compare our baseline estimates (column 1) with spatial inequality (column 2). Since our measures of ethnic inequality are derived based on geographic data rather than on household surveys, our indicator may reflect the growth effect of regional disparities in income that are not related to ethnicity. For the construction of spatial inequality, we use corrected nighttime lights and compute inequality in average per capita luminosity between first-level administrative units. This procedure yields proxies of spatial inequality (in Appendix A.4, we provide a detailed description on the construction of spatial inequality, document descriptive statistics, and show the relationship to ethnic inequality). The results of column (2) suggest that between-region inequality is significantly associated with underdevelopment. In column (3), we examine which dimension of inequality, ethnic or spatial, dominates. The results suggest that both variables have a negative impact on economic growth that is significant at the 5% level.

In column (4) we address the argument that measures of spatial inequality derived by cross-regional disparities in per capita luminosity may produce biased results because of large differences in land size and population size between countries. The effects of ethnic and spatial inequality are, however, relatively unaffected when we introduce controls for population and land area. In column (5) we examine whether the results change when we use population-weighted ethnic inequality, with little changes in inferences.

In columns (6)–(8), we jointly include our measure of ethnic inequality and dimensions of population-related inequality. We first examine whether cross-country differences in population size play a role (column 6), with little effect on inferences. In column (7) we control for inequality in population size across ethnic homelands to test for the hypothesis that our ethnic Gini is driven by skewness in the spatial distribution of the population. Consistent with the moderate correlation of the variables (about 45% for Gini(NW) and 25% for Gini(W)), there is no change in the parameter estimate of ethnic inequality, but the estimate of population inequality is statistically indistinguishable from zero. In columns (7) we investigate whether our results reflect the fractionalization of ethnic groups. There is a large literature studying the consequences of ethnic fractionalization on development (Easterly and Levine, 1997; Alesina et al., 2003; Montalvo and Reynal-Querol, 2005a; Montalvo and Reynal-Querol, 2021; see Alesina and La Ferrara, 2005 for an overview). We use the geocoded population data underlying our ethnic inequality measures to compute indices of ethnic fractionalization for the period 1992–2013 (a detailed description of the construction and the relation to ethnic inequality is given in Appendix A.5). Conditioning on ethnic fractionalization has no effect on the parameter estimate of ethnic inequality, but ethnic fractionalization enters with a statistically insignificant estimate.

Overall, the results of Table (C-10) show that the negative empirical relationship between ethnic inequality and development is not driven by other dimensions of the distribution of the population across space and groups.

3.3.5 Heterogeneity across geographic regions

We also examine heterogeneity in the effect of ethnic inequality on economic growth across geographic regions; for brevity, we report and discuss these results in Appendix A.6. This set of results shows that ethnic inequality hampers growth regardless of the geographic region, but the effect is strongest for Africa, Asia, and the Americas.

4 Sub-national ethnic inequality and causal identification

A remaining threat to identification comes from unobserved factors that potentially confound our results. To the extent that these unobservables are time-invariant, they are eliminated by the country fixed effects. To the extent that these unobservables are correlated with past developments of GDP, they are absorbed by the included GDP dynamics. A threat may be that there are unobserved time-varying factors that are either not correlated with past GDP or that exert influence over a period that exceeds the time dimension of our modeled GDP process.

In the next step, we develop a strategy to address the potential presence of time-varying omitted factors that may simultaneously influence ethnic inequality and real per capita GDP. To this end, we construct a unique dataset of ethnic inequality for first-level administrative regions (ADM1). ADM1 units are regional administrative regions hierarchically organized directly below the central government, usually "provinces" or "states". Our sub-national dataset includes 3,609 ADM1 regions observed between 1992 and 2013, resulting in a total of 66,912 region-year observations. We then combine our data with data on Gross Regional Products (GPR). Official statistics on GRP are typically not available or comparable for sub-national units on a global scale. The dominant approach to obtain estimates for economic growth on the sub-national level is to use per capita nighttime light intensity to construct regional GRP measures (see, e.g., Leßmann and Seidel, 2017; Bruederle and Hodler, 2018; Hirte et al., 2020). We use

GRP measures from Leßmann and Seidel (2017), which are available for 180 countries between 1992 and 2012. Descriptive statistics of ethnic inequality on the regional level are presented in Appendix A.7.

Our sub-national analysis has three favorable features that allow us to address the potential confounding influence of unobservables. First, while our country-level estimates account for time-invariant unobservables on the country-level, exploiting sub-national variation also allows us to account for heterogeneity across regions within countries. Second, the sub-national perspective allows us to eliminate all time-varying unobservables on the country-level by including a full set of country-year fixed effects. A remaining threat to identifying a causal effect is that there are omitted confounders that vary across time and across subnational-units. The third and most important advantage of the sub-national perspective is that it allows us to exploit the spatial distribution of ethnic homelands across sub-national administrative borders to construct an instrumental variable for ethnic inequality.

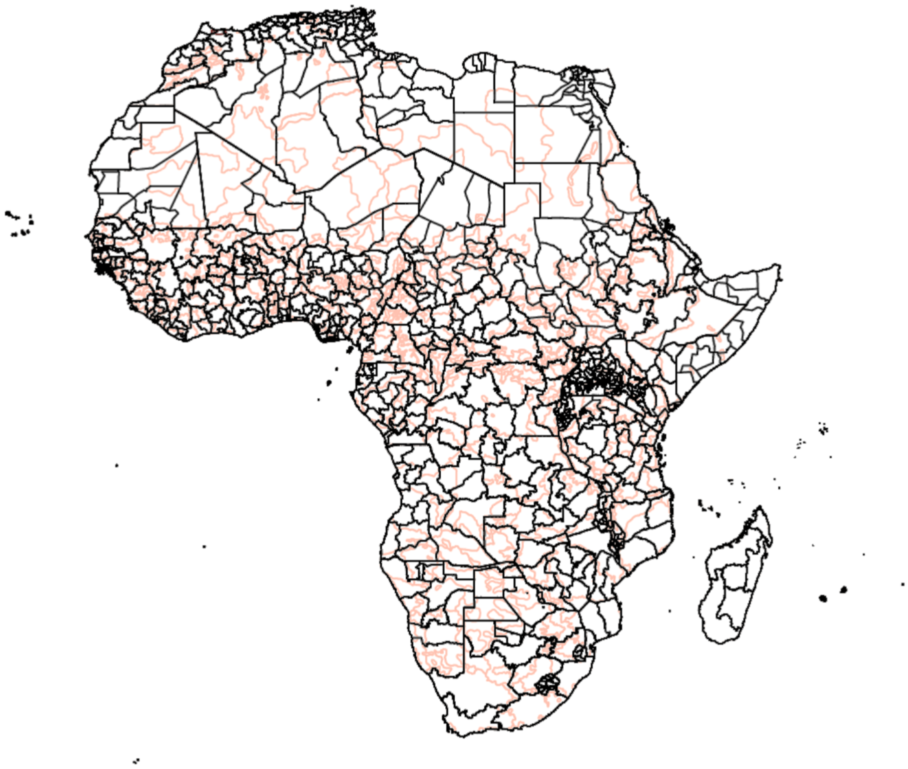
4.1 Sub-national border artificiality

Many developing countries across the world have inherited an artificial mapping of borders from colonial times. These artificial borders are especially prevalent in Africa, where most national borders have been artificially designed by European colonizers during the 1880s and 1890s, partitioning more than 200 ethnic groups across two or more countries. While these artificial designs on the national level are well known and have been exploited for empirical studies (for an overview, see Michalopoulos and Papaioannou, 2020), border artificiality is similarly pronounced on the sub-national level.[16]

In many countries in the world, first-level administrative areas are far from matching ethnic borders. Figure (5) shows the discrepancy between ethnic homelands and ADM1 borders for Africa, where such differences between ethnic and administrative borders are particularly prevalent. In many instances, the internal borders that African countries inherited from their colonizers were as arbitrary as their national borders. Even today, most sub-national borders are still identical to the former colonial creations, also dividing populations (Ramutsindela, 2019). A Prominent historical example is Nigeria, where the British created two regions that are separated exactly by the 7°10' line of Latitude. While some of these borders have been redrafted over the past decades and centuries, colonial borders have largely been left unchanged in many other countries such as Namibia or Kenya. For Africa, the reason for the large inertia of sub-national borders is rooted in the *uti possidetis* principle adopted by the Organization of the African Unity, demanding that newly-formed sovereign states should retain the internal borders of colonial times (Justin and De Vries, 2019). In particular, many of the ADM1 regions still follow straight lines. Even though some historical internal borders have been reformed, Figure (5) reveals that the reformers clearly did not systematically take into account ethnic homelands when recreating administrative units. When examining country case studies, there seems to be no clear pattern in how and why internal borders have been redrafted (Justin and De Vries, 2019). Figures (B-9)–(B-13) in the appendix provide complementary evidence for the rest of

[16]Of the 907 ethnic groups include in our dataset, 755 groups (83.24%) are partitioned by sub-national borders, while only 152 groups (16.76%) are located in a single ADM1 region.

Figure 5 SUB-NATIONAL BORDER-ARTIFICIALITY IN AFRICA, ADM1-REGIONS AND ETHNIC HOMELANDS



Notes: The figure shows the extent of sub-national border artificiality in Africa. Illustrated is the spatial distribution of ethnic homelands (visualized via orange lines) and first-level administrative units (ADM1, visualized via black lines) for the African continent. The figure refers to the political situation of the year 2013, the most recent period included in our sample. Data on sub-national administrative units is obtained from the GADM database of Global Administrative Areas (GADM, 2018).

the world. The data shows that border artificiality is a widespread phenomenon globally, also affecting sub-national units in other parts of the world.

An important assumption of our sub-national strategy is that internal borders of ADM1 regions constitute an appropriate unit of analysis to explore the growth effect of ethnic inequality. We argue that this is the case because ADM1 borders are both stable and politically relevant. During our period of observation, ADM1 borders have been unchanged in approximately 70% of countries included in our sample. The internal border changes that took place—mostly during the 1990s—were usually not related to ethnic factors (see Cunningham and Weidmann, 2010 for a detailed discussion).[17] ADM1 units are also politically relevant: in about two thirds of the countries in our sample, the ADM1-level of government is a site of electoral competition (Treisman, 2007). Theoretically, usage of georeferenced data allows us to go down to any political or geographic unit (until the pixel-level). We use the first sub-national administrative unit because these units are politically most relevant.

[17]Our results show that the estimates are not sensitive to excluding or including regions with border changes.

4.2 Construction of our spatial instrumental variable

For our sub-national analysis, we first focus on the African continent and later provide complementary suggestive evidence also for the rest of the world. This decision is based on the particular prevalence of sub-national border artificiality in Africa. This artificiality causes nearly all of the African ethnic groups in our dataset (202 out of 218) to be scattered through at least two different sub-national regions. Moreover, previous work has shown that national border demarcations in Africa are orthogonal to ethnic groups' characteristics (Michalopoulos and Papaioannou, 2016), which we can confirm for the sub-national level (results available upon request).

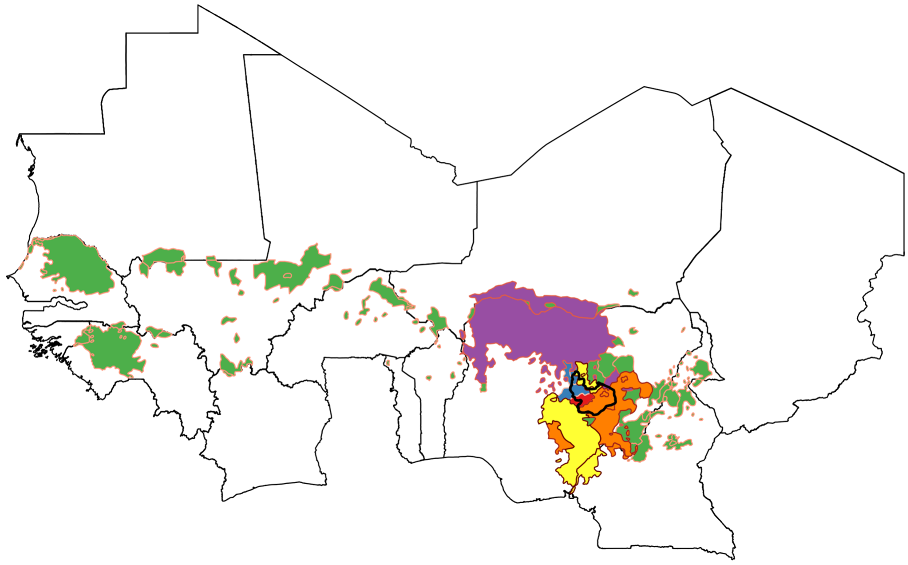
Consider ethnic groups $e_s = 1, \ldots, E$ that are located in sub-national unit s. As ADM1 borders partition ethnic homelands in numerous cases, only a fraction of the members of a group e_s live in s (p_{e_s}), and another fraction lives in ADM1 units s' outside s (1 - p_{e_s}). These "outside-units" can be located in the same or in other countries. The share of group members living in outside-units is in fact high. In our dataset, the share of individuals living in inside-units, p_{e_s}, is about 12%, and 88% of group members live in outside-units.

Historical and geographic factors have led to relatively homogeneous *within-group* incomes and sizable *between-group* income differentials. Hence, the correlation of incomes between members of the same group that are distributed across sub-national units is high (about 50% in our dataset). The average sub-national income level, however, is measured only within ADM1 borders, and incomes of group e earned by members living in outside-units are not included in per capita GRP of s. We exploit this exclusion to construct an instrumental variable for sub-national ethnic inequality. In the first step, we compute per capita incomes for members of e_s that live in outside-units. We use nighttime lights measured in those homeland parts of e_s that are located in outside-units and divide it by the population of group members living in these units ("outside-incomes"). In the second step, we use outside-incomes of all e_s living in s and compute a Gini index of inequality (Z_{ist}) following our general approach of Equation (1).

Figure (6) provides an illustration of our construction process based on Plateau, an ADM1 region of Nigeria. There are six ethnic groups in Plateau, and their homelands, represented by colored areas, extent well beyond the borders of Plateau (marked with thick black lines). Our sub-national-measure of ethnic inequality uses per capita income differentials across those members of the depicted groups that live within the borders of Plateau. The instrumental variable for Plateau uses per capita incomes of all members of the six ethnic groups that live in outside-units, i.e. in colored areas outside Plateau. We use their incomes to construct a between-group inequality measure of a counterfactual Plateau outside its administrative borders. As incomes in outside-units are correlated with incomes in inside-units, we can expect outside-inequality to be (strongly) correlated with inside-inequality.

Exclusion restriction: The exclusion restriction of our spatial instrumental variable requires that GRP in unit s is not affected by outside-inequality through channels other than the narrow causal pathway of influencing ethnic inequality in s. This assumption is plausible, as the instrumental variable mixes information on many individuals to an "artificial" Gini index of outside-inequality with no real geographic meaning. Also, outside-units mostly spread over several ADM1 regions and often also over multiple countries. The wide geographic distribution of

Figure 6 CONSTRUCTION OF THE SPATIAL INSTRUMENT OF ETHNIC INEQUALITY, ILLUSTRATION USING THE ADM1-REGION OF PLATEAU (NIGERIA)



Notes: The figure illustrates the construction process underlying our approach to compute an instrumental variable for sub-national levels of ethnic inequality. The figure visualizes a map of the ADM1 regions in Nigeria (political situation as of the year 2013, the latest year included in our sample). The area in the center of the figure, marked by thick black lines, is the ADM1 unit Plateau. The ethnic homelands located in this unit are represented by different colors and refer to the homelands of the Tiv (yellow), the Fulbe (green), Birom and Jerawa (blue), the Angas (red), Jukun and Idoma (orange), and the Hausa (purple). The figure illustrates that these ethnic groups are distributed over many of Nigeria's other ADM1 units, and that there is rich heterogeneity in the spatial distribution of Plateaus's ethnic groups over these "outside units". The instrumental variable approach utilized for our sub-national analysis uses per capita income of these outside units (as suggested by corrected series of nighttime lights) to compute an artificial counterfactual of the level of ethnic inequality in Plateau.

outside-units mitigates the threat that there are (un)observed factors that are systematically correlated with inequality between outside-groups and per capita incomes in unit s. To nevertheless account for potential violations of the exclusion restriction, we specify versions of our instrumental variable approach that account for spatial correlation. The exclusion restriction does *not* require that incomes earned in s' should not be correlated with s, it only requires that inequality across all outside-units should not influence production in s.

4.3 First-stage results

Figure (B-14) in the appendix shows that our sub-national measure of ethnic inequality is positively and significantly correlated with the spatial instrumental variable (80.5% in the sample of African regions and 78.5% in the full sample of region-years). In Panel B of Table (3), we present the first-stage relationships that underlie our 2SLS estimates. The parameter estimate of our excluded instrumental variable is positive (0.953 in our benchmark model) and statistically significant at the 1% level. The sizable Kleibergen-Paap F-statistic, which provides robust weak instrument diagnostics in case that errors are not i.i.d., strongly rejects the presence of weak instruments.[18] The minimum requirement of the 2SLS model is that the instrumental variable is "relevant" and the model is not underidentified. Our weak identification tests (Kleibergen-Paap rk LM tests) reject the null of underidentification ($F > 500$; $p = 0.000$) for each specification (not reported). We also conduct several weak-instrument-robust tests of the null $\hat{\beta} = 0$ that are fully robust to weak instruments (we report results from the Stock-Wright S test in Table 3). These tests deliver p-values of 0.000 for each specification.

Taken together, these and further instrument diagnostics suggest that our spatial instrumental variable is suitable to identify the effect of sub-national ethnic inequality on economic growth.[19]

4.4 Regression results (second stage)

In Panel A of Table (3), we present (second-stage) regression results on the effect of sub-national ethnic inequality on economic growth in Africa. We report results of traditional within-group estimates as references (labeled "FE-OLS") and compare the outcomes with our instrumental variable strategy (labeled "2SLS"). For both estimators, we present results from three model specifications. The first model ("Benchmark") replicates our baseline dynamic panel data specification of Equation (4)

$$y_{ist} = \beta \text{Gini}^{e}_{ist} + \sum_{j=1}^{\phi} \omega_j y_{ist-j} + \eta_i + \zeta_t + \varepsilon_{ist}, \tag{9}$$

where y_{ist} is real per capita GRP in sub-national unit s of country i at time t. The first stage of our 2SLS setting is given by

$$\text{Gini}^{e}_{ist} = \sum_{j=1}^{\phi} \pi y_{ist-j} + \rho Z_{ist} + \lambda_i + \varrho_t + u_{ist}. \tag{10}$$

The parameter estimate ($\hat{\beta}$) of sub-national ethnic inequality for the within group estimator (column 1) is negative and statistically significant at the 1% level ($t = 7.53$). This result is consistent with the country-level estimates, suggesting that ethnic inequality yields negative growth effects on both the country level and the sub-national level. The coefficient on ethnic inequality remains negative in column (2) when we employ 2SLS estimates of the benchmark dynamic panel data model. For both estimation strategies, the coefficient on sub-national ethnic inequality is statistically significant at the 1% level. Numerically, the parameter estimate increases by about 20% when we instrument ethnic inequality by our spatial instrument.

A concern of the country-level results is that the results may be confounded by time-varying unobservables that are correlated simultaneously with ethnic inequality and economic growth. The advantage of the sub-national perspective is that we can explicitly account for time-varying unobservables on the country-level by including country-year fixed effects. We present these

[18] With one endogenous regressor, the test statistic is identical to the first-stage F statistics often used to evaluate the strengths of instruments.

[19] We also carefully conducted further tests, including the Olea and Pflüger (2013) test that allows for errors that are not conditionally homoskedastic and serially uncorrelated. Also, we assess whether inferences change if our instrument would only be "plausibly exogenous" (Conley et al., 2012). These tests all underscore that our 2SLS results are valid; for brevity, we do not separately report them.

Table 3 ETHNIC INEQUALITY AND ECONOMIC GROWTH—SUB-NATIONAL ESTIMATES, AFRICAN REGIONS, 1992–2012

Dependent variable: Real per capita GRP, log(GRP^{pc})						
	Benchmark		**Country-Year FE**		**Spatial Correlation**	
	FE-OLS (1)	2SLS (2)	FE-OLS (3)	2SLS (4)	FE-OLS (5)	2SLS (6)
	Panel A: Regression results (second stage)					
Ethnic inequality	-0.0354***	-0.0450***	-0.00623***	-0.00826***	-0.00625***	-0.00816***
	(0.0047)	(0.0072)	(0.0016)	(0.0022)	(0.0016)	(0.0022)
log(GRP^{pc})$(t-1)$	0.741***	0.738***	0.710***	0.709***	0.710***	0.709***
	(0.0449)	(0.0448)	(0.0265)	(0.0264)	(0.0265)	(0.0264)
log(GRP^{pc})$(t-2)$	0.216***	0.216***	0.172***	0.172***	0.173***	0.172***
	(0.0510)	(0.0508)	(0.0225)	(0.0225)	(0.0225)	(0.0224)
log(GRP^{pc})$(t-3)$	-0.00446	-0.00410	0.0611**	0.0610**	0.0611**	0.0610**
	(0.0177)	(0.0177)	(0.0286)	(0.0286)	(0.0286)	(0.0286)
log(GRP^{pc})$(t-4)$	-0.0354***	-0.0450***	-0.00623***	-0.00826***	-0.00625***	-0.00816***
	(0.0047)	(0.0072)	(0.0016)	(0.0022)	(0.0016)	(0.0022)
	Panel B: First-stage regression results					
Spatial Instrument	–	0.953***	–	0.916***	–	0.917***
		(0.0473)		(0.0515)		(0.0513)
Observations	9,280	9,280	9,280	9,280	9,280	9,280
Sub-national Units	589	589	589	589	589	589
R-Squared	0.908	0.908	0.985	0.985	0.985	0.985
F Stat (second)	4399	4210	107273	107713	91480	91756
K-P F-Stat (first)	–	405	–	317	–	320
S-Y 10% max IV size	–	16.38	–	16.38	–	16.38
S-W p-val	–	0.000	–	0.000	–	0.000
Country Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Period Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Country-Year Fixed Effects	No	No	Yes	Yes	Yes	Yes
Spatial Correlation	No	No	No	No	Yes	Yes

Notes: Cluster robust standard errors (on the ADM1 level) are reported in parentheses. The dependent variable is the log of real per capita GRP, measured using data from Leßmann and Seidel (2017). Ethnic inequality is measured as described in Section (2) using differences in nighttime lights across ethnic homelands. The table presents estimates from three models, each estimated with the traditional within group estimator (columns labeled "FE-OLS") and with 2SLS using our spatial instrumental variable. The first model ("Benchmark") replicates the specification of the country-level dynamic panel data model of Section (3.2), the second specification ("Country-Year FE") accounts for time-varying unobservables on the country level by including country-year fixed effects. The third specification ("Spatial Correlation") accounts for spatial correlation between the GRP of sub-national units and a the average of GRP in other sub-national units of the same country, weighted by the inverse of the distance between sub-national units. The row labeled "K-P F-Stat (first)" reports the F-statistic of the Kleibergen-Paap rk Wald test, which is a robust test for weak identification in case the errors are not i.i.d. We also report Stock-Yogo thresholds for the Kleibergen-Paap weak identification test for a demanding critical value of 10% max IV size (labeled "S-Y 10% max IV size"). The row labeled "S-W p-val" presents p-values of the Stock-Wright LM test, presenting weak-instrument-robust inference. The null of this test is that the endogenous regressor is equal to zero. The test is robust to the presence of weak instruments.

*** Significant at the 1 percent level,
** Significant at the 5 percent level,
* Significant at the 10 percent level

estimates in columns (3)–(4), where we augment model (9) by fixed effects for country-years ($\nu_i \times \mu_t$) and estimate

$$y_{ist} = \beta \text{Gini}^e_{ist} + \sum_{j=1}^{\phi} \omega_j y_{ist-j} + \eta_i + \zeta_t + (\nu_i \times \mu_t) + \varepsilon_{ist}. \tag{11}$$

The coefficient on ethnic inequality retains its economic and statistical significance in both the FE-OLS and the 2SLS model. Including country-year fixed effects eliminates a large portion of the variation in the data. The estimated coefficients on ethnic inequality hence decline when we account for unobserved time-varying factors on the country level.

Our exclusion restriction requires that income inequality across individuals that live outside of s but that belong to ethnic groups located in s has no impact on sub-national development through channels other than the correlation with ethnic inequality in s. This assumption is plausible, as our instrumental variable is an artificial measure, and individuals included in this measures often live in multiple countries with limited potential for direct interactions. Nevertheless, it is a concern that there are regional economic variables that are correlated simultaneously with our artificial measure of ethnic inequality and sub-national GRP of s. Such variables can violate our exclusion restriction if they spread across sub-national units. As a third specification, we allow for a spatial correlation of GRP and GRP shocks to tackle the threat posed by regionally correlated omitted variables. Specifically, we model spatial interdependence across sub-national units by including a weighted average $\mathbb{W}^s y_{it}$ of GRP in other sub-national units

$$y_{ist} = \beta \text{Gini}^e_{ist} + \sum_{j=1}^{\phi} \omega_j y_{ist-j} + \eta_i + \zeta_t + \psi \mathbb{W}^s y_{it} + (\nu_i \times \mu_t) + \varepsilon_{ist}. \tag{12}$$

where $\mathbb{W}^s$ is the matrix of inverse distances between s and other sub-national units of the same country.[20] There is little change in the effect size when we account for spatial lags (columns 5–6). Inferences also do not change if we additionally instrument the spatial lag by four of its temporal lags (often referred to as "S-2SLS", not reported).

Numerically, the cumulative long-run effect found in the fully specified model for Africa is comparable to the estimates obtained in our country-level exercises. Computing long-run effects according to equation (6), the coefficients suggest that a permanent transition from a society where ethnicity plays no role for incomes to a society with the largest possible level of ethnic inequality reduces per capita GDP in Africa by about 12.5% (Column 4 of Table 3).

Alternative variant of ethnic inequality: Table (C-12) in the appendix shows the results for our weighted variant of ethnic inequality. The effect of ethnic inequality remains negative and statistically significant at the 1% level when we account for relative population size. The estimated effect size increases compared to the benchmark estimates obtained for non-weighted ethnic inequality.

[20] We use average distances from the center of s to the centers of all other sub-national units of the same country and compute the inverse of this distance to obtain weights. The rationale for this weighting scheme is that we expect closer sub-national unit to exert greater spatial interdependence. See Lee (2017) for a detailed description of spatial panel models.

Accounting for border changes: A concern about our instrumental variable strategy is that the results may be influenced by sub-national units that experienced border changes during our sample period. In Table (C-13) we present re-estimates of our benchmark sub-national models in which we exclude regions in which borders have changed during our sample period. This strategy yields a loss of 1,711 observations. The results are statistically not distinguishable from our benchmark results.

4.5 Robustness of the sub-national results

In Table (C-14), we explore whether the sub-national results are robust to methodological changes of our spatial instrument. We construct an alternative variant of our instrument that exploits information only from individuals that live in outside-units in other countries. The rationale is that we might expect that interactions between members of the same ethnic group are less pronounced when group members live in other countries. Altering the construction of our instrument does not change the results. The estimated parameters remain negative and statistically significant at the 1%.

Our baseline sub-national estimates use cluster-robust standard errors at the ADM1 level, following the practice to cluster at the lowest possible level (Cameron and Miller, 2015). In Table (C-15) we assess the robustness of our results when we cluster at the country-level, in Table (C-16), we use two-way clustering to model standard errors nested in countries and regions. Doing so has little impact on the results.

Similar to the cross-national results, a concern of our sub-national estimates may be that the results are driven by a skewed distribution of the population across ethnic homelands. We construct Gini indices of population inequality on the ADM1 level to test whether this is the case. Accounting for population inequality in our benchmark model does not change the inferences (C-17).

4.6 Results for the rest of the world

To provide a complete view on the effect of ethnic inequality on sub-national economic growth, Table (C-18) in the appendix presents re-estimates of the baseline sub-national specifications using data for all global regions. In Tables (C-19)–(C-25), we report additional results, replicating all robustness checks conducted for African regions. The results all provide strong suggestive evidence for a negative effect of ethnic inequality on economic growth also in other parts of the world.

We also present evidence for specific geographic units. Our description in Section (2.5) shows that ethnic inequality is particularly large in Africa, Asia, and Latin America, and less pronounced in Europe and in Northern America. Relatedly, the maps of ADM1 regions (Figures 5 and B-10-B-13) suggest that border artificiality is widespread in most parts of the world, but less so in Europe.

When re-estimating our models excluding European (Table C-26) and European and Northern American (Table C-27) regions, we do not observe changes in inferences. In Tables (C-28) and (C-29), we narrow the focus on Asian and Latin American sub-national regions. In all these specifications, the results point to a negative effect of ethnic inequality on economic growth that is economically and statistically significant.

5 Mechanisms

Finally, we use our design to explore mechanisms via which ethnic inequality transmits to growth. Our panel dataset allows us to go beyond cross-sectional correlations and to account for cross-country heterogeneity in unobserved factors in the transmission mechanism. To exploit the advantages of the panel structure, we focus on conflict and the provision of public goods, while we exclude other possible channels such as trust (Hodler et al., 2020) and party ethnification (Huber and Suryanarayan, 2016; Houle, 2018). Data on these variables is not available for a sufficiently large sample of countries and years to estimate a dynamic panel data model.[21]

For the empirical specification, we follow Acemoglu et al. (2019), examining the link between ethnic inequality and our transmission channels m_{it} via

$$m_{it} = \beta \text{Gini}_{it}^{e} + \sum_{j=1}^{\phi} \omega_j y_{it-j} + \sum_{j=1}^{\phi} \alpha_j m_{it-j} + \eta_i + \zeta_t + \varepsilon_{it}. \tag{13}$$

The model includes four lags of GDP to account for the confounding influence of past economic conditions on both the propensity of conflicts and the demand for public goods. By similar arguments as those raised in Section (3.2), we also account for the dynamic process of the transmission variables four years prior to t.

Weighted versus non-weighted ethnic inequality: Our analysis shows that both non-weighted and weighted ethnic inequality are negatively related to growth. However, we find differences in the effect size across both variants. We hypothesize that this is the case because accounting for group size uncovers different aspects of the transmission mechanism from ethnic inequality to growth. For conflict, it should not matter much if wealth differences on the group level diminish when we account for population size. Any such differences should matter for conflict, as it is unlikely to assume that smaller groups tend to radicalize and force conflict to a lesser extent than larger groups if they are left behind. For the provision of public goods, however, group size potentially matters. Larger income differentials across ethnic groups complicates a consensus about the types and the extents of public goods that should be provided. In democratic regimes, smaller groups are less influential in political decision making. Hence, we expect our weighted measure to more adequately capture the relationship between ethnic inequality and the provision of public goods.

Ethnic inequality and conflict: Previous studies have shown that ethnic groups with income levels above or below the country average (Cederman et al., 2011) or with valuable mines in their homelands (Berman et al., 2017) are more likely to be involved in conflict. In a similar vein, inequality between ethnic groups has been shown to increase the probability of coups d'état

[21] Our measures of ethnic inequality are negatively correlated with trust in a pooled cross-section analysis but we do not find a statistically robust relationship between ethnic inequality and party ethnification in a cross-sectional setting. Results are available on request.

Table 4 TRANSMISSION MECHANISMS OF ETHNIC INEQUALITY TO GROWTH—DYNAMIC PANEL DATA ESTIMATES, 1992–2012

Dependent variables: Conflict (Deaths per 1,000) and Index of Public Goods						
	Channel I: Conflict			**Channel II: Public Goods**		
	(1)	(2)	(3)	(4)	(5)	(6)
Gini(NW)	0.494***		0.474**	-0.145*		-0.0891
	(0.171)		(0.204)	(0.0731)		(0.0836)
Gini (W)		0.507	0.0713		-0.383***	-0.301**
		(0.347)	(0.420)		(0.117)	(0.139)
Observations	3,444	3,444	3,444	2,076	2,076	2,076
Countries	162	162	162	143	143	143
R-Squared	0.094	0.091	0.094	0.688	0.688	0.688
F Stat	8.582	8.082	8.395	124.0	128.3	122.9
Country Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Period Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Cluster robust standard errors are reported in parentheses. The dependent variables are (i) conflict intensity, measured by UCDP-PRIO (Gleditsch et al., 2002) and Bluhm et al. (2020) and (ii) the provision of public goods, computed following the method of Baldwin and Huber (2010) (see Appendix A.7 for details). Each model includes fixed effects for countries and years and includes four lags of the dependent variable and four lags of per capita GDP. Ethnic inequality is measured as described in Section (2) using differences in nighttime lights across ethnic homelands. The ethnic inequality measures used in the table are: our version of ethnic inequality using corrected light data (Gini(NW)) and our version of ethnic inequality using corrected light data and weights for the size of ethnic groups (Gini(W)).

*** Significant at the 1 percent level,
** Significant at the 5 percent level,
* Significant at the 10 percent level

(Houle and Bodea, 2017). Using data for a cross-section of 39 countries, Østby (2008) shows that ethnic inequality and conflict are positively correlated. Closest to our analysis is the study of Lessmann and Steinkraus (2019), who find a positive correlation between resource-based ethnic inequality and violent conflicts. We advance on these findings in three points. First, we consider the overall level of ethnic inequality rather than resource-based ethnic inequality. Second, our analysis has a larger temporal coverage, including observations from the 1990s. Accounting for pre-2000 dynamics is potentially important, given that both average levels of ethnic inequality and the number of violent conflicts were higher than in the post-2000 period. Third, we examine the role of group size for the outbreak of conflicts. While we hypothesize that ethnic inequality increases the tendency for conflict regardless of whether between group inequality is driven by small or large ethnicities, there is no evidence in prior studies for whether weighted or non-weighted ethnic inequality is more decisive for conflict. We measure the extent of civil conflict by the number of battle-related deaths (per 1,000 inhabitants) obtained from Bluhm et al. (2020).

Ethnic inequality and public goods: Previous evidence suggests that ethnic inequality is correlated with the provision of public good in a cross-section of 69 countries (Baldwin and Huber, 2010). Again, the key advantage of our panel dataset is that we can account for time-invariant unobservables and that our model is based on a larger sample of countries and years. To model the amount of public goods provision, we compute an index for the broadest possible sample of countries and years following Baldwin and Huber (2010) (see Appendix A.7 for a detailed description). We exclude autocracies, as the possibility to influence the provision of public goods via voting should be heavily limited in autocratic regimes.

Results for the transmission mechanisms: The results for our transmission mechanisms are presented in Table (4). Columns (1)–(3) report results for conflict, columns (4)–(6) show results for public goods provision. Consistent with our hypotheses, ethnic inequality is positively associated with conflict, but the parameter estimate is statistically significant at conventional levels only for our non-weighted measure.

The results in columns (IV)—(VI) suggest that both variants of ethnic inequality are negatively related to the provision of public goods, but the parameter is larger in size for weighted ethnic inequality. The "horse race" in column (6) corroborates our hypothesis that accounting for group size matters when examining the link between ethnic inequality and public goods provision.

Taken together, we draw two conclusions from the analysis of transmission channels. First, the cross-sectional correlations reported in previous studies are robust and reappear also when examining the influence of ethnic inequality on conflict and public goods in a dynamic panel data setting. Given that our estimates are based on data from three decades, the results also suggest that the correlations reported in previous studies are not period-specific. Second, the parameter estimates for weighted and non-weighted ethnic inequality imply that the transmission channels differ in the extent to which group size influences the effects of ethnic inequality. Hence, when examining the causes and consequences of ethnic inequality, it is important (i) to have a theoretical foundation about how ethnic inequality should be related to the outcome variable of interest and (ii) to account for group size if necessary by using the weighted-variant of ethnic inequality.

6 Conclusions

Motivated by the limited availability of ethnic inequality measures, we have compiled comparable Gini indices of income disparities across ethnic groups for the broadest possible sample of countries, sub-national regions, and years. We have shown that a fundamental requirement for creating harmonized measures of between group inequality is adjusting the nighttime lights obtained by the DMSP's satellites to account for ill-calibration and top-coding. Based on our measures, we document cross-country differences and trends in ethnic inequality since the early 1990s. Our empirical estimates on the effect of ethnic inequality on economic growth deliver two key results. First, our main result is that ethnic inequality reduces economic growth, both on the country-level and on the sub-national level. The effect is robust to changes in the construction of our measures and the employed estimation technique. Second, we showed that ethnic inequality channels to growth by influencing conflict and the provision of public goods.

Our results provide important policy implications for developing countries, suggesting that policies that aim to reduce income disparities across ethnic groups may foster economic development. However, our results also imply that such policies may only be beneficial to growth if they do not fuel further tensions between ethnic groups. As the transmission channels feature a high degree of persistence and primarily influence economic development in the long-term, we may also expect that equalizing policies may only unfold their effect in the long-run.

We provide our ethnic inequality measures for the research community, and hope that the utilization of these measures improves our understanding about the causes and consequences of ethnic inequality.

A. Supplementary Notes

A.1 The Li and Zhou (2017) approach to calibrate nighttime lights

We follow the approach of Li and Zhou (2017) to calibrate the raw stable nighttime lights series, which augments the IRQR method of Elvidge et al. (2009). The method consists of four steps.

In **Step 1** we conduct a systematic adjustment of the underestimation of satellite F14 to make it consistent with the trajectory of F10 and F12. Given that F12 and F14 have composites for the overlaid years (see Table C-1), we compute the relationship between these satellites via the second-order regression model (Elvidge et al., 2009)

$$\mathrm{DN}_{ref} = \psi_0 + \psi_1 \mathrm{DN} + \psi_2 \mathrm{DN}^2, \tag{14}$$

where DN_{ref} and DN denote nighttime lights from F12 and F14.

In **Step 2**, we correct the underestimation of F15 in years 2003–2007 to make it comparable with the trajectory of F14 and its predecessors (2000-2002). This adjustment is based on all lit pixels in F15-2003 and the calibrated F14-2003 to modify the systematic underestimation of F15-2003–F15-2007.

In **Step 3**, we adopt the widely-used approach to calibrate the data based on the reference image of Sicily (Italy) to calibrate the nighttime lights of F16. As F16 does not show a temporally consistent pattern, we also adjust its series, as the comparison with the temporally overlaying F15 shows that F16 suffers from an overall underestimation. We use the lit images of F15-2007 and F16-2007 to establish the relationship between the two satellites.

Finally, in **Step 4**, we adjust the extremely high observations of F18-2010 in order to make it consistent with the overall trend. Again, we use the second order regression model to bring together calibrated F16-2009 with F18-2010.

A.2 Relation of our ethnic inequality measures to the Gini index of Alesina et al. (2016)

Our approach to construct measures of ethnic inequality builds on AMP, who construct similar measures for a cross-section of countries. Our method predominantly deviates from the AMP approach by using harmonized NTL series to compute comparable time-series of ethnic inequality.

In Figure (A-1), we examine how ethnic inequality measures change when using adjusted NTL data. Our country examples in Section (2.4.2) show that differences between raw and adjusted NTL series are asynchronously distributed across geographic regions. A change in measured ethnic inequality hence depends on (i) the extent to which the calibration process affects the implied relative income levels across ethnic homelands, (ii) the degree of truncation in the original data, and (iii) the extent to which various ethnic groups at different positions in the national income distribution are affected.

Figure (A-1) shows that there are substantial differences in ethnic inequality between our harmonized Gini indices and the original series from AMP. The mean level of ethnic inequal-

Figure A-1 COMPARISON OF ETHNIC INEQUALITY MEASURES, 2000
Notes: The figure compares the original measures of ethnic inequality of AMP, obtained vie raw nighttime light series from the DMSP-OLS with our indices that use adjusted nighttime lights. The original AMP measures are on the y-axis, the non-weighted Gini index of ethnic inequality (GiniNW, left-hand side) and the population-weighted Gini index of ethnic inequality (GiniW, right-hand side) are on the x-axis. The red line is the angle bisector to facilitate comparison of the Gini indices, blue dots are ethnic inequality levels.

ity suggested by the AMP measure is 0.424, which is about 10 Gini points larger than our non-weighted index and about 30 Gini-points larger than our population-weighted index. The Gini index of AMP is larger than our non-weighted measure in approximately three-fourths of cases, but using adjusted nighttime lights also leads to higher levels of ethnic inequality in some instances. When we account for the size of groups, however, the Gini indices are lower for the overwhelming majority of countries ($> 99\%$), and higher only in rare cases with low levels of ethnic inequality.[22]

A.3 Description of the design of our nonparametric estimator

We first consider a general semiparametric version of our dynamic panel data model (see Libois and Verardi, 2013). For illustration purposes, we simplify the notation of the model to

$$y_{it} = \mathbf{X}_{it}\boldsymbol{\theta} + f(\text{Gini}^e_{it}) + \eta_i + \varepsilon_{it},\ i = 1, \dots, N,\ t = 1, \dots, T\, T << N, \tag{15}$$

where GDP dynamics and period effects are included in the matrix $\mathbf{X}$ and $f(\text{Gini}^e_{it})$ describes a nonparameterized function of ethnic inequality that can assume any form. The fixed effect can be eliminated by differentiation over time

[22] We also compared our index to other measures of ethnic inequality. Most importantly, we constructed survey-based ethnic inequality indices using data from the World Value Survey (WVS), which includes both the ethnicity and the income level of about 200,000 respondents. The correlation of the resulting survey-based Gini index (population-weighted) and our geospatial index is about 45%, which we cautiously interpret as additional evidence for the accuracy of our method. However, members of ethnic minorities are heavily underrepresented in the WVS, resulting in an (asynchronous) downward-bias of the survey-based Gini index.

$$y_{it} - y_{it-1} = (\mathbf{X}_{it} - \mathbf{X}_{it-1})\boldsymbol{\theta} + \{f(\text{Gini}^e_{it}) - f(\text{Gini}^e_{it-1})\} + \varepsilon_{it} - \varepsilon_{it-1}. \tag{16}$$

A key challenge of Equation (16) is to find the unknown function $G \equiv \{f(\text{Gini}^e_{it}) - f(\text{Gini}^e_{it-1})\}$. We follow Baltagi and Lee (2002) and approximate G by series $p^k(\text{Gini}^e)$, where $p^k(\cdot)$ are the first k terms of a sequence of functions $[p_1(\text{Gini}^e), p_2(\text{Gini}^e), \ldots]$. Equation (16) then becomes

$$y_{it} - y_{it-1} = (\mathbf{X}_{it} - \mathbf{X}_{it-1})\boldsymbol{\theta} + \{p^k(\text{Gini}^e_{it}) - p^k(\text{Gini}^e_{it-1})\}\gamma + \varepsilon_{it} - \varepsilon_{it-1}, \tag{17}$$

which can consistently be estimated with OLS. We then use the estimates $\hat{\theta}$ and $\hat{\gamma}$, fit the fixed effects and $\hat{\eta}$ and estimate the error component residual in Equation (15)

$$\hat{u}_{it} = y_{it} - \mathbf{X}_{it}\boldsymbol{\theta} - \hat{\eta} = f(\text{Gini}^e) + \varepsilon_{it}. \tag{18}$$

We then follow Libois and Verardi (2013) and fit the curve $f(\cdot)$ by regressing $\hat{u}_{it}$ on Gini^e using local–constant kernel regressions with Gaussian kernels. We follow Li and Racine (2004) and select the bandwith (determines the bias and variance of the mean function estimator) using cross-validation. The reported marginal effects in Table (C-4) are average derivatives of y_{it} with regard to Gini^e. We then use 100 bootstrapping iterations to obtain standard errors (Cattaneo and Jansson, 2018).

A.4 Spatial inequality: Measurement, descriptive statistics, and relationship to ethnic inequality

We compute a measure of spatial inequality that is based on first level administrative units. Data comes from the GADM database version 3.6 released in Mai 2018 (GADM, 2018), which includes observations for 386,735 administrative areas on the globe. We measure spatial inequality across 3,609 first administrative sub-level regions in the period 1992–2013 using our adjusted nighttime lights series.

The average level of spatial inequality in 2013 is 36%, which closely resembles the mean level of ethnic inequality (35%). However, the correlation between the two variables is only 44%, which suggests that both indices reflect different forms of inequality. In particular, the standard deviation of ethnic inequality (25%) is lower than that of spatial inequality (20%). An important difference between both measures is that the Gini index of ethnic inequality is 0 if there exists only a single ethnic group, but the level of spatial inequality is nonzero for each observation. The lowest levels of spatial inequality in 2013 are reached in Poland (6%), the Czech Republic (7%), Lithuania (8%), and Luxembourg (8%). On the other end of the spectrum, the highest levels are observed in Chad (94%), Mali (88%), and Myanmar (87%). The case of Myanmar is particularly interesting, because although ethnic inequality is above-average (54%), it is still considerably lower than spatial inequality (overall household inequality is below the world mean (46%) and the Asian mean of 43%).

Figure (A-2) shows the overall relationship between ethnic inequality and spatial inequality in 2013. As expected, the figure implies a positive relationship between the variables, but this relationship is far from perfect.

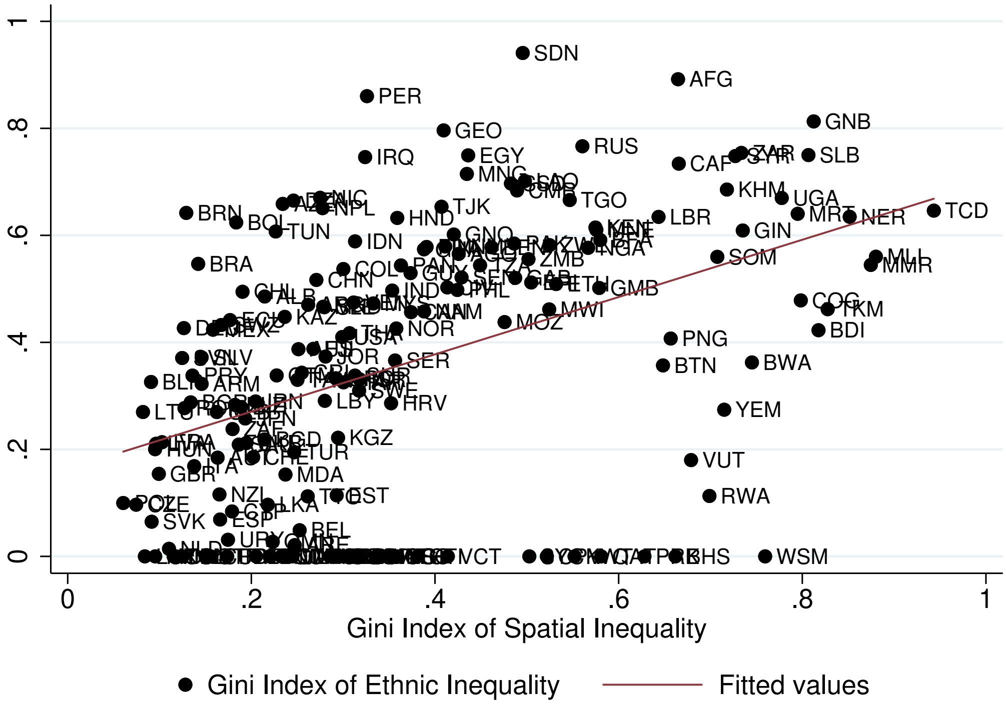


Figure A-2 THE RELATIONSHIP BETWEEN ETHNIC INEQUALITY AND SPATIAL INEQUALITY, 2013
Notes: The figure shows the relationship between ethnic inequality and spatial inequality. Spatial inequality is measured based on 3,609 first administrative sub-level regions using our adjusted series on nighttime lights and spatial information from (GADM, 2018). The figure shows the relationship in the year 2013, the latest period of our sample.

A.5 Computation of our index of ethnic fractionalization

We use the standard ELF measure to compute an index of ethnic fractionalization for the most broadest possible sample of countries and years (see Greenberg, 1956). To maximize coverage, we utilize geocoded data on the spatial distribution and composition of the population. Specifically, ethnic fractionalization can be calculated for each country via the ELF approach using

$$\text{ELF} = 1 - \sum_{i=e}^{n} p_e^2,\ e = \{1, \ldots, n\} \tag{19}$$

where p_e denotes the share of population that belongs to ethnic group e. Intuitively, ELF measures the probability that two randomly selected individuals within a country belong to different ethnic groups. We chose this measure over the alternatives (in particular, indices of ethnic polarization), as it increases with n, whereas indices of ethnic polarization typically reach their maximum for $n = 2$. Figure (B-8) shows how ethnic inequality and our measure of ethnic fractionalization are related. There is some correlation between the variables, suggesting that countries with higher levels of ethnic fractionalization also tend to have higher income disparities across ethnic groups. However, there are many cases in which ethnic inequality substantially differs from ethnic fractionalization.

A.6 Geographic heterogeneity in the growth effect of ethnic inequality

Our baseline estimates draw on all available country-year observations to construct a sample with maximum size. Given the global geographic differences in the extent of ethnic inequality, there may be heterogeneity in the growth effect of ethnic inequality across geographic units. In particular, ethnic inequality may predominantly have negative effects in countries where ethnic diversity is large, and less so in other regions of the world. Figure (A-3) shows geographical patterns in the relationship between ethnic inequality and economic development. African countries are clustered at lower levels of economic development and higher level of ethnic inequality, whereas European countries have higher average levels of per capita GDP and lower ethnic inequality. Countries from South America are located between these extremes, while countries from Asia and the rest of the Americas span the entire spectrum.

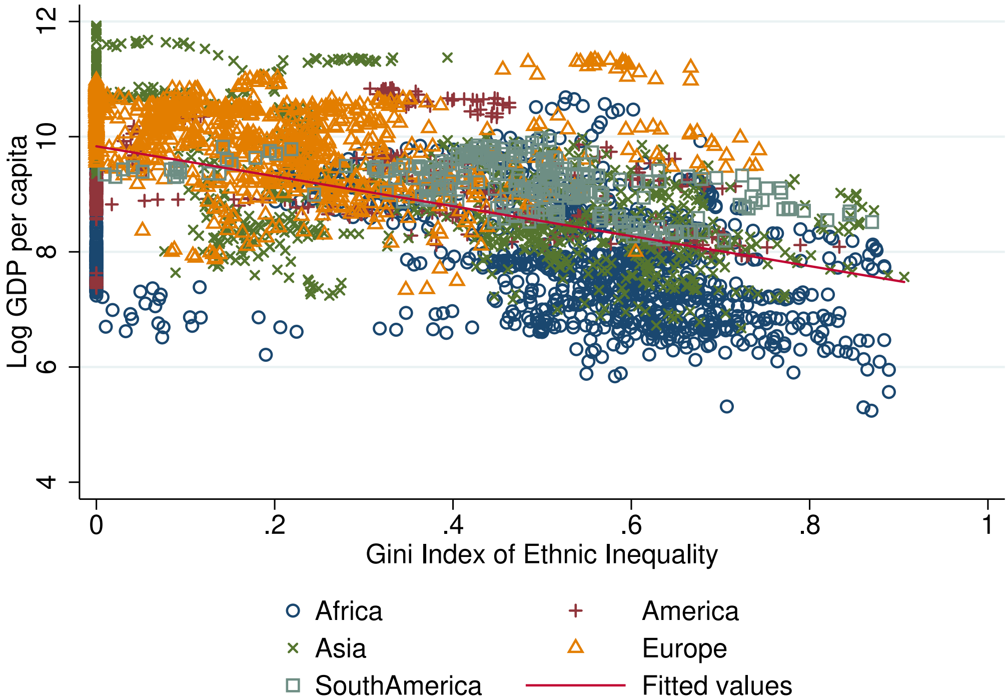


Figure A-3 The relationship between ethnic inequality and economic development, and the role of geographic location. The figure plots the log of per capita GDP and the non-weighted Gini index of ethnic inequality for all aountry-year observations in our sample. Countries are colored to reflect the continent on which they are located.

We re-estimate our baseline dynamic panel data model separately for continents to examine geographic heterogeneity in the effect of ethnic inequality on growth (Table C-11 in the appendix). The results suggest that ethnic inequality is negatively related to development in almost all parts of the world. The effect is, however, strongest for Africa, Asia, and parts of the Americas.

A.7 Descriptive statistics of sub-national ethnic inequality

Our sub-national ethnic inequality measure can be computed for 3,609 administrative regions between 1992 and 2013, resulting in 66,912 region-year observations. The mean level of ethnic inequality implied by this measure is 21.9%, which is somewhat lower than on the national level

(36.8%). However, the coefficient of variation is 115% and points to a substantially larger variation than in the case of country-level ethnic inequality (72%). Sub-national ethnic inequality is highest in the Amazonas (Brazil, 91%); Ituri (Democratic Republic of the Kongo, 89%); Luang Namtha (Laos, 89%); Maluku Utara (Indonesia, 89%); Krasnojarsk (Russia, 88%); Manyara (Tanzania, 88%); and Xizang (China, 88%).

A.8 Computation of our index of public goods provision on the national level

Our measure on the provision of public goods is constructed similar to the approach introduced by Baldwin and Huber (2010). They use ten different variables from the World Bank's World Development Indicators (WDI) database (World Bank, 2020), including measures for public health, education, public infrastructure and the governments' taxing capacity to compile their measure of public goods. However, these time series vary considerably in their availability. To achieve a sufficiently large sample to conduct our dynamic panel data analysis, we build on five key variables from Baldwin and Huber (2010) that are available for a large sample of countries and years: (i) the percentage of children immunized against measles and DPT with age between twelve and 23, (ii) improved sanitation facilities, (iii) improved water source, and (iv) telephone lines per 100 people. While the neglected variables range in their availability between 1,643 and 3,057 country-year observations in the relevant time period between 1992 and 2013 (or, in case of "procedures to enforce a contract" are not available anymore), our five variables allow for inclusion of 5,163 and 5,563 observations. In contrast to Baldwin and Huber, who compute a time-invariant average over the 1996–2006 period, our goal is to construct a continuous yearly measure for our panel estimates.

We conduct a factor analysis based on our five variables to create our public goods variable. If one of the five variables is missing, we use the value of the factor analysis of the other four variables. This procedure considerably increases the number of observations. Reassuringly, the loss of information that occurs because of the drop of the five Huber-Baldwin dimensions is minimal: the correlation between our measure and the Huber-Baldwin index is 94.94% if we compute a similar average of our variable for the 1996–2006 period.

B. Supplementary Figures

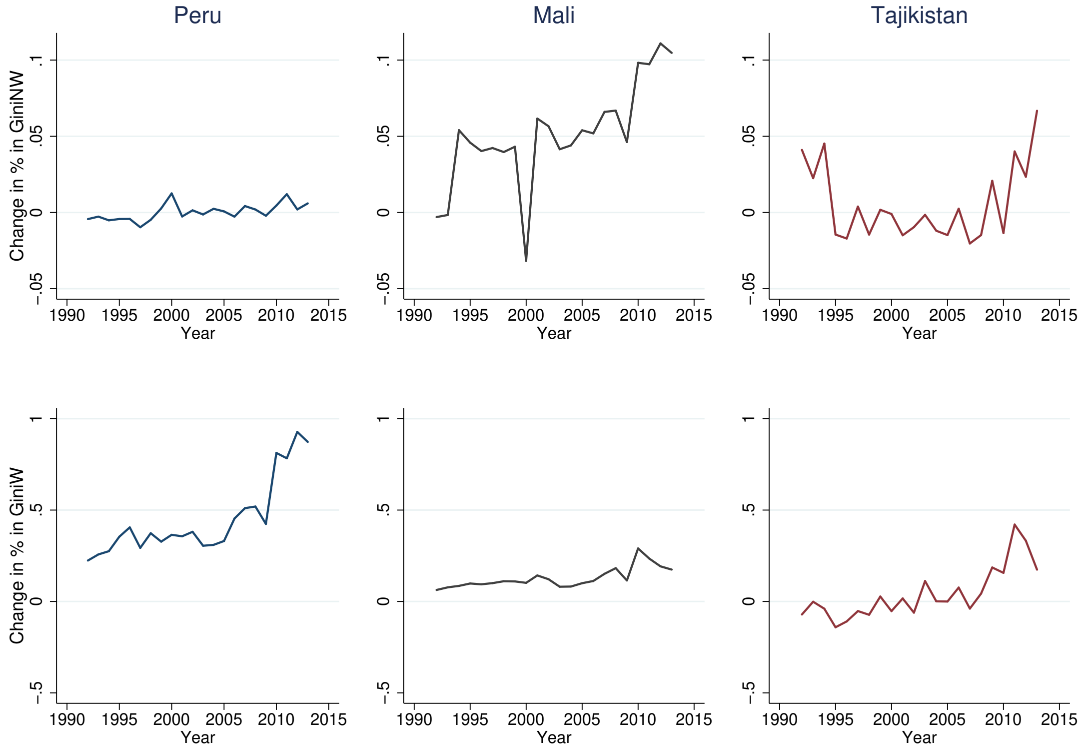


Figure B-1 EFFECTS OF CALIBRATING NTL SERIES AND REMOVING TOP-CODING ON MEASURED LEVELS ON ETHNIC INEQUALITY OVER TIME, 1992–2012

Notes: The figure shows how the Gini of ethnic inequality changes when we remove top coding and apply our calibration process relative to the Gini that results from using raw NTL series. The upper row shows changes for the non-weighted measure of ethnic inequality, the lower row shows results for population-weighted ethnic inequality. Changes are shown for the three expository countries, but they are similarly asynchronous in the large majority of countries.

Figure B-2 RELATIONSHIP BETWEEN THE GINI COEFFICIENT OF ETHNIC INEQUALITY (NON-WEIGHTED) AND THE GINI COEFFICIENT OF INCOME INEQUALITY, 2013
Notes: The figures shows the correlation between non-weighted ethnic inequality and inequality of disposable incomes (taken from the SWIID, version 6.2) in the year 2013. The coefficient of correlation is 31.37% in 2013 (39.31% when only taking into account levels of ethnic inequality greater than 0), and 23.98% (34.01% for nonzero values) when considering the whole sample of country-year observations.

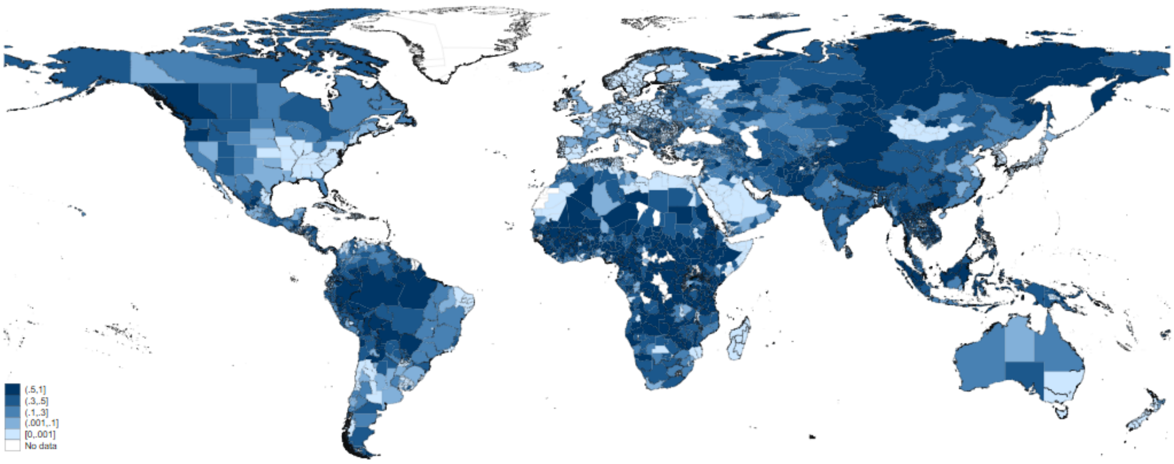


Figure B-3 ETHINC INEQUALITY AT THE SUB-NATIONAL LEVEL IN 2013. The figure shows the spatial distribution of $\text{Gini}^{e}_{\text{GPW}}$ across 3,609 first level administrative regions. For details on the construction of the measure, see Section (2.3).

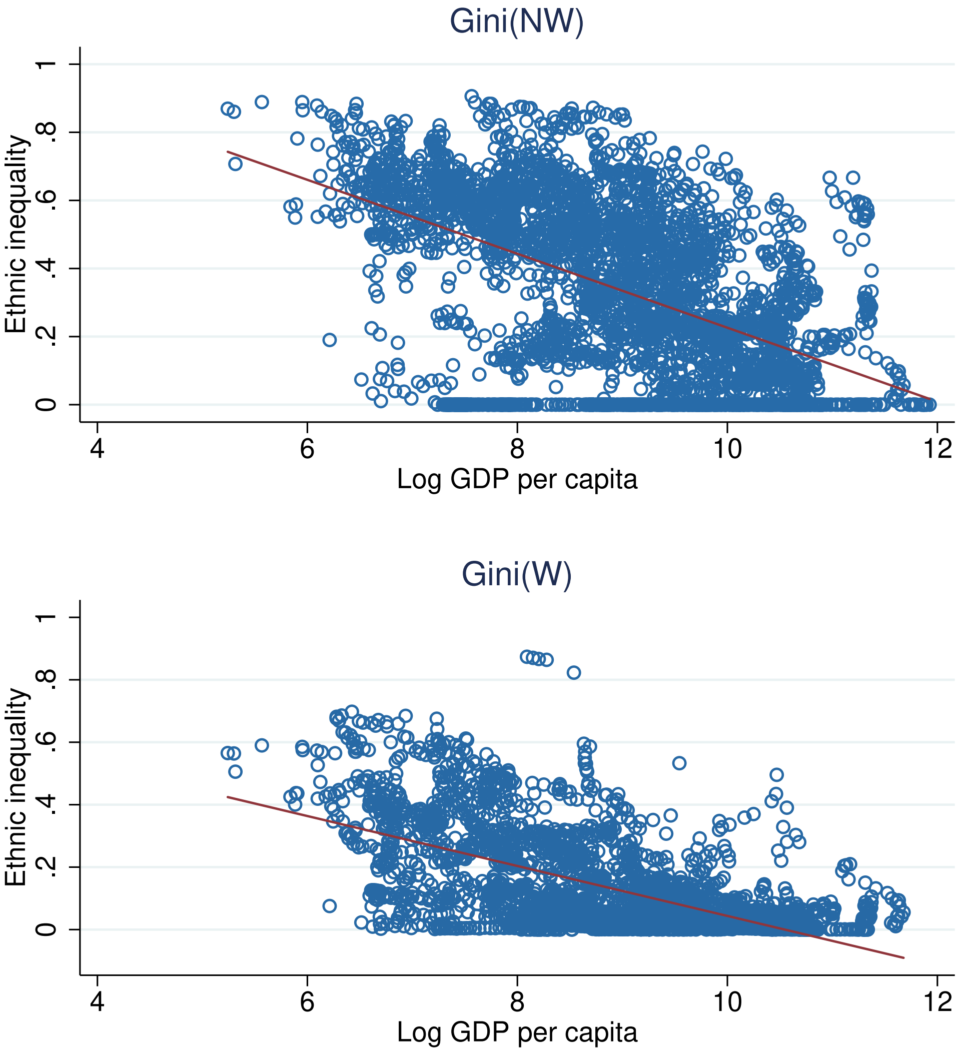


Figure B-4 UNCONDITIONAL CORRELATION OF ETHNIC INEQUALITY AND ECONOMIC DEVELOPMENT, 1992–2012
Notes: Correlation between non-weighted ethnic inequality (left panel) and population-weighted ethnic inequality (right panel). The correlation is -53.3% for non-weighted ethnic inequality and -58.4% for population-weighted ethnic inequality.

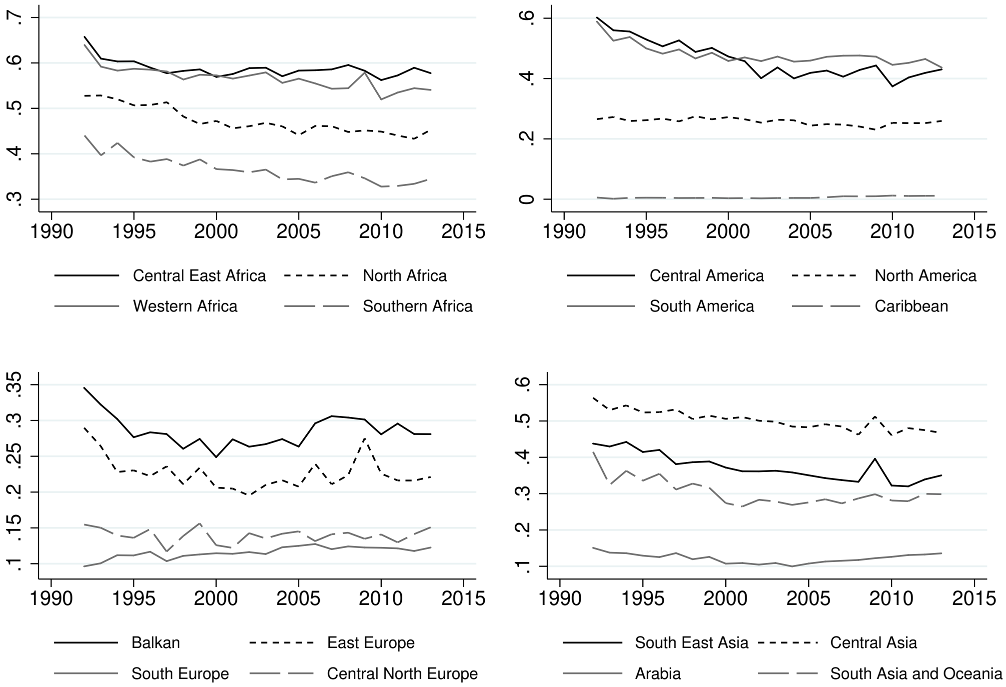


Figure B-5 DEVELOPMENT OF ETHNIC INEQUALITY OVER TIME, NON-WEIGHTED GINI, GINI(NW), 1992–2013
Notes: The figure shows the development of our non-weighted measure of ethnic inequality by region and over time for the full period for which data is available (1992–2013).

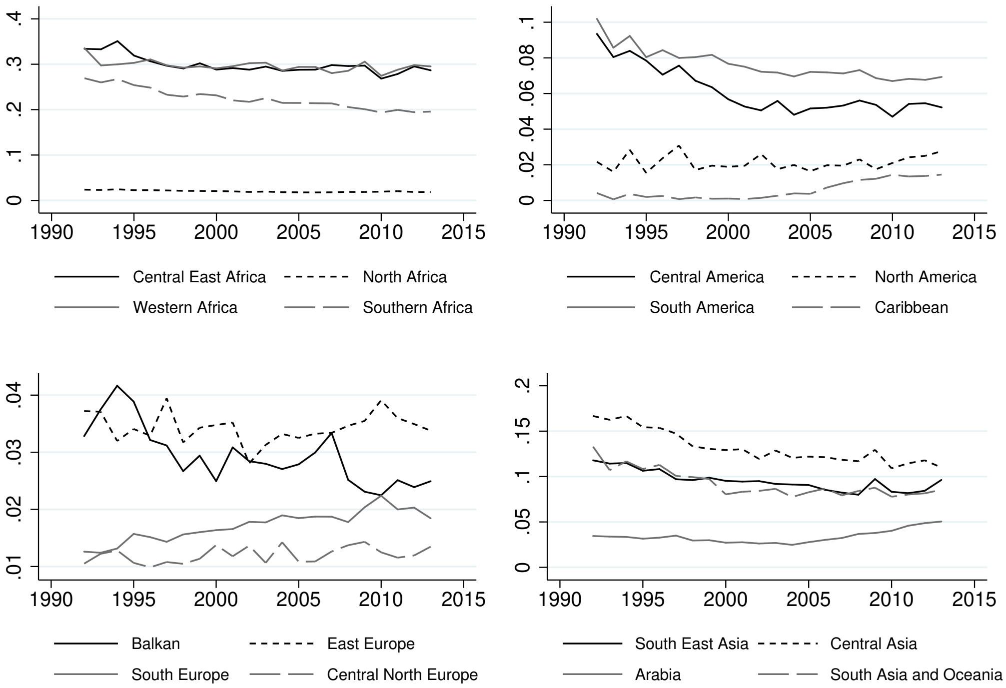


Figure B-6 DEVELOPMENT OF ETHNIC INEQUALITY OVER TIME, WEIGHTED GINI, GINI(W), 1992–2013
Notes: The figure shows the development of our population-weighted measure of ethnic inequality by region and over time for the full period for which data is available (1992–2013).

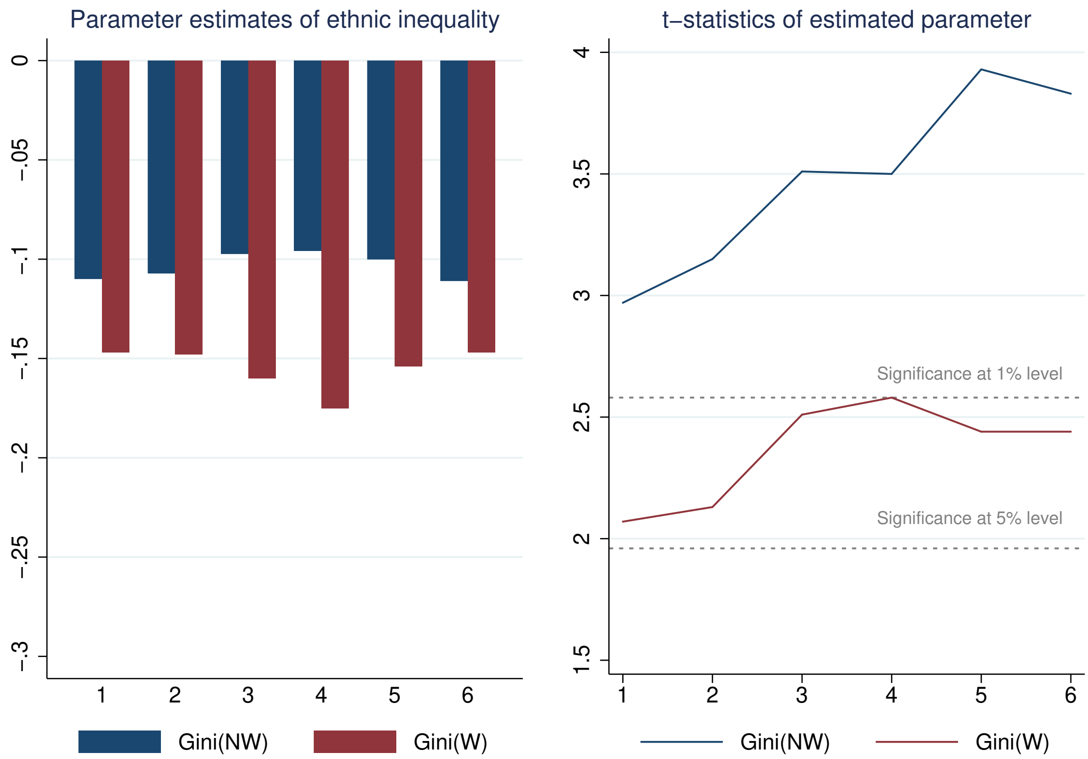


Figure B-7 THE INFLUENCE OF GDP DYNAMICS ON PARAMETER ESTIMATES OF ETHNIC INEQUALITY

Notes: The figure shows the estimated parameters (left-hand side) and the t-statistics (right-hand side) for GDP dynamics that include a maximum (ϕ) of between 1 and 6 lags of real per capita GDP (depicted on the x-axis). Results are computed using variants of Equation (4) with $\phi = 1, \ldots, 6$ and are reported for Gini(NW) and Gini(W).

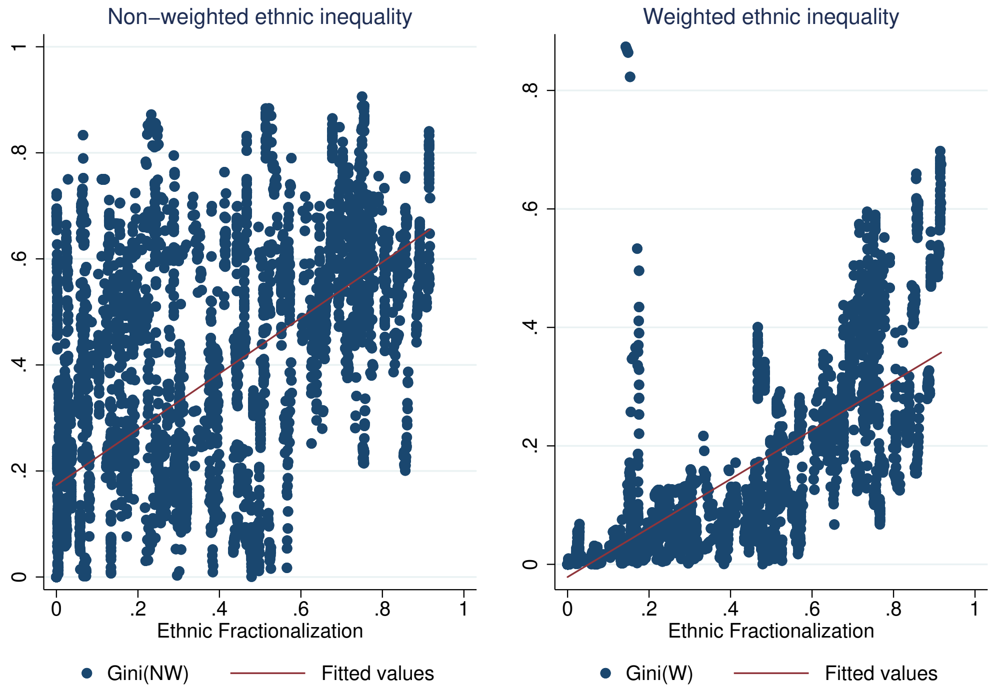


Figure B-8 ETHNIC INEQUALITY AND ETHNIC FRACTIONALIZATION
Notes: The figure shows the relationship between ethnic inequality, measured by our non-weighted and population-weighted Gini indices, and the degree of ethnic fractionalization.

Figure B-9 ADM1-REGIONS AND ETHNIC HOMELANDS, SOUTH AMERICA
Notes: The figure shows the spatial distribution of ethnic homelands (orange lines) and first-level administrative units (black lines) for Asia. The figure refers to the political situation of 2013.

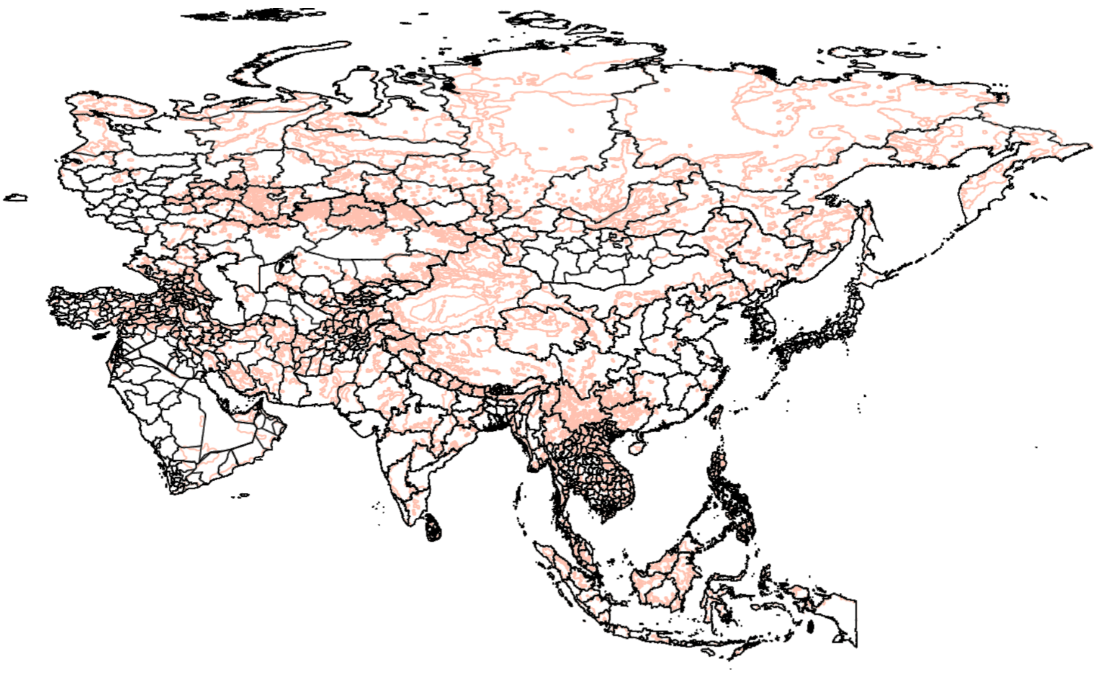


Figure B-10 ADM1-REGIONS AND ETHNIC HOMELANDS, ASIA
Notes: The figure shows the spatial distribution of ethnic homelands (orange lines) and first-level administrative units (black lines) for Asia. The figure refers to the political situation of 2013.

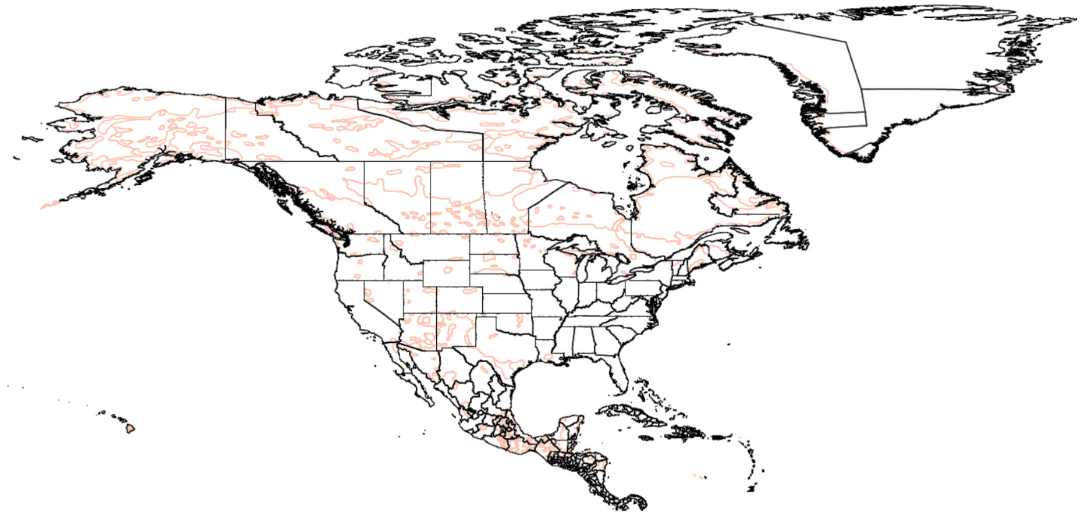


Figure B-11 ADM1-REGIONS AND ETHNIC HOMELANDS, NORTH AMERICA
Notes: The figure shows the spatial distribution of ethnic homelands (orange lines) and first-level administrative units (black lines) for North America. The figure refers to the political situation of 2013.

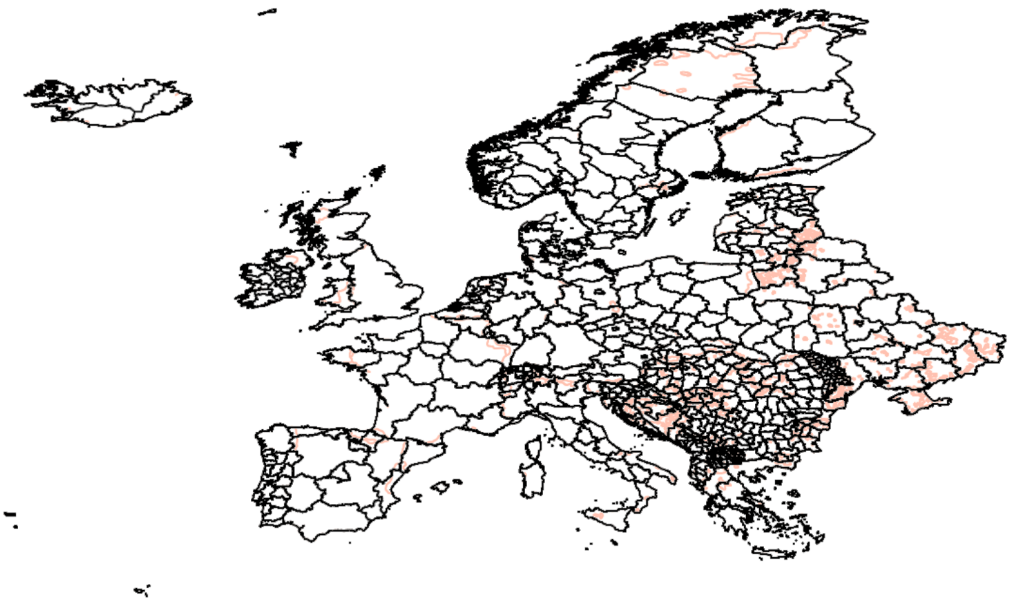


Figure B-12 ADM1-REGIONS AND ETHNIC HOMELANDS, EUROPE
Notes: The figure shows the spatial distribution of ethnic homelands (orange lines) and first-level administrative units (black lines) for Europe. The figure refers to the political situation of 2013.

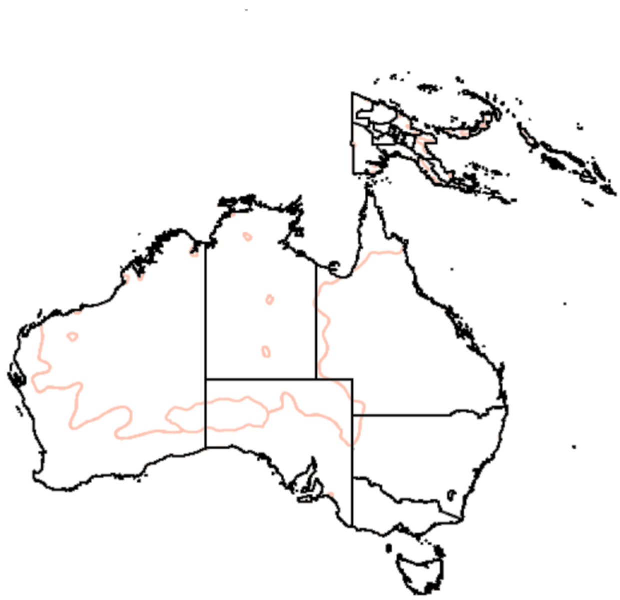


Figure B-13 ADM1-REGIONS AND ETHNIC HOMELANDS, OCEANIA
Notes: The figure shows the spatial distribution of ethnic homelands (orange lines) and first-level administrative units (black lines) for Oceania. The figure refers to the political situation of 2013.

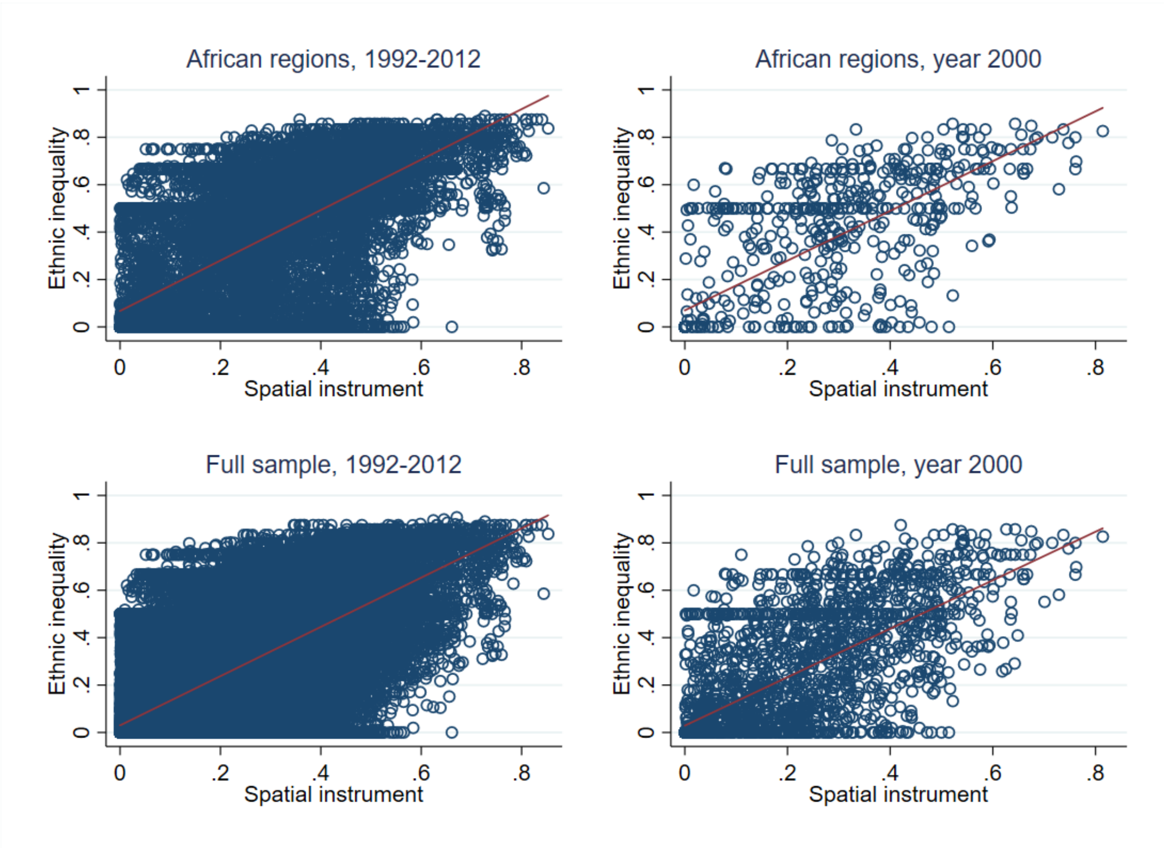


Figure B-14 CORRELATION BETWEEN ETHNIC INEQUALITY AND THE SPATIAL INSTRUMENTAL VARIABLE

Notes: The figure shows the correlation between our sub-national measure of ethnic inequality and our spatial instrumental variable for African regions (figures in the upper panel) and the full sample of regions (lower panel). The graphs on the left-hand side show the correlation for the full sample of region-years, the graphs on the right-hand side show the correlations for the year 2000 (about the middle of our sample). The correlation between sub-national ethnic inequality and the spatial instrument for Africa is 80.5% (full sample of African regions) and 81.1% (African regions in the year 2000). In the full sample of regions, the correlation is 78.4% (full sample) and 78.6% (full sample in the year 2000).

C. Supplementary Tables

Table C-1 SATELLITE COMPONENTS OF THE STABLE LIGHTS SERIES OF THE DEFENSE METEOROLOGICAL SATELLITE PROGRAM / OPERATIONAL LINESCAN SYSTEM NIGHTTIME LIGHTS (DMSP/OLS NTL)

Year			**Satellite No.**			
1992	F10					
1993	F10					
1994	F10	F12				
1995		F12				
1996		F12				
1997		F12	F14			
1998		F12	F14			
1999		F12	F14			
2000			F14	F15		
2001			F14	F15		
2002			F14	F15		
2003			F14	F15		
2004				F15	F16	
2005				F15	F16	
2006				F15	F16	
2007				F15	F16	
2008					F16	
2009					F16	
2010						F18
2011						F18
2012						F18
2013						F18

Notes: The table shows which satellite components have been orbiting earth at which years in our dataset. At several instances, nighttime lights were derived from two satellites. We use all images of the DMSP/OLS nighttime light series to obtain a temporally consistent dataset.

Table C-2 LIST OF COUNTRIES, NUMBER OF ETHNIC GROUPS (E), AND GINI INDICES OF ETHNIC INEQUALITY, NON-WEIGHTED MEASURES, GINI(NW)

Country	E	Gini	Country	E	Gini	Country	E	Gini	Country	E	Gini
Afghan.	22	0.86	Dom. Rep.	1	0.00	Liberia	9	0.62	Sao Tome	1	0.00
Albania	5	0.33	Ecuador	6	0.38	Libya	4	0.35	Saudi Arabia	2	0.06
Algeria	8	0.49	Egypt	4	0.67	Liechtenstein	1	0.00	Senegal	11	0.47
Andorra	1	0.00	El Salvador	4	0.38	Lithuania	5	0.24	Serbia	11	0.23
Angola	13	0.52	Eq. Guinea	3	0.51	Luxembourg	1	0.00	Seychelles	1	0.00
Antigua	1	0.00	Eritrea	10	0.57	Macedonia	5	0.42	Sierra Leone	6	0.46
Argentina	12	0.42	Estonia	2	0.15	Madagascar	1	0.00	Singapore	1	0.00
Armenia	7	0.38	Ethiopia	17	0.49	Malawi	5	0.47	Slovakia	4	0.11
Australia	3	0.41	Fiji	2	0.33	Malaysia	20	0.44	Slovenia	3	0.25
Austria	4	0.11	Finland	4	0.39	Mali	10	0.55	Solomon Is.	4	0.75
Azerbaijan	15	0.50	France	8	0.26	Malta	1	0.00	Somalia	4	0.66
Bahamas	1	0.00	Gabon	7	0.51	Mauritania	4	0.63	South Africa	13	0.23
Bahrain	1	0.00	Gambia	3	0.45	Mauritius	1	0.00	South Korea	1	0.00
Bangladesh	3	0.21	Georgia	15	0.64	Mexico	40	0.37	South Sudan	19	0.71
Belarus	5	0.35	Germany	4	0.18	Micronesia	2	0.12	Spain	4	0.08
Belgium	3	0.06	Ghana	12	0.56	Moldova	5	0.15	Sri Lanka	3	0.12
Belize	4	0.22	Greece	5	0.31	Monaco	1	0.00	St. Lucia	1	0.00
Benin	9	0.60	Grenada	1	0.00	Mongolia	15	0.67	St. Vincen	1	0.00
Bhutan	9	0.35	Guatemala	17	0.40	Montenegro	5	0.44	Sudan	19	0.76
Bolivia	16	0.57	Guinea	10	0.56	Morocco	7	0.24	Suriname	5	0.28
Bosnia	4	0.26	Guinea-Bis.	9	0.82	Mozambique	9	0.49	Swaziland	3	0.35
Botswana	6	0.28	Guyana	5	0.53	Namibia	8	0.44	Sweden	3	0.35
Brazil	50	0.51	Haiti	1	0.00	Nauru	1	0.00	Switzerland	4	0.18
Brunei	5	0.24	Honduras	7	0.58	Nepal	16	0.62	Syria	7	0.33
Bulgaria	4	0.24	Hungary	7	0.22	Netherlands	2	0.00	Taiwan	2	0.21
Burkina Faso	15	0.57	Iceland	1	0.00	New Zealand	2	0.08	Tajikistan	15	0.60
Myanmar	20	0.53	India	58	0.46	Nicaragua	7	0.64	Tanzania	30	0.51
Burundi	2	0.42	Indonesia	92	0.65	Niger	11	0.66	Thailand	18	0.34
Cambodia	12	0.65	Iran	27	0.25	Nigeria	28	0.57	Togo	11	0.66
Cameroon	20	0.59	Iraq	8	0.23	Norway	3	0.56	Tonga	1	0.00
Canada	20	0.45	Ireland	1	0.00	Oman	2	0.05	Trin. & Tob.	3	0.12
Cape Verde	1	0.00	Israel	3	0.22	Pakistan	16	0.54	Tunisia	3	0.51
Cen. Afr. Rep.	11	0.73	Italy	8	0.13	Palestina	2	0.08	Turkey	10	0.13
Chad	17	0.64	Ivory Coast	12	0.48	Panama	8	0.54	Turkmenist.	6	0.61
Chile	8	0.50	Jamaica	1	0.00	P.-N. Guinea	6	0.34	Uganda	14	0.68
China	57	0.48	Japan	2	0.23	Paraguay	9	0.24	Ukraine	12	0.16
Colombia	17	0.53	Jordan	2	0.25	Peru	14	0.66	UAE	2	0.21
Comoros	1	0.00	Kazakhstan	17	0.50	Philippines	35	0.48	UK	6	0.14
Costa Rica	8	0.31	Kenya	16	0.62	Poland	2	0.11	USA	28	0.33
Croatia	7	0.18	North Korea	1	0.00	Portugal	1	0.00	Uruguay	3	0.14
Cuba	1	0.00	Kosovo	4	0.00	Qatar	1	0.00	Uzbekistan	11	0.14
Cyprus	2	0.08	Kuwait	1	0.00	Rep. Congo	10	0.56	Vanuatu	2	0.18
Czech Rep.	3	0.08	Kyrgyzstan	9	0.23	Romania	11	0.23	Venezuela	9	0.47
Dem. Congo	31	0.74	Laos	19	0.62	Russia	82	0.62	Vietnam	35	0.58
Denmark	1	0.00	Latvia	7	0.24	Rwanda	2	0.12	Yemen	2	0.29
Djibouti	1	0.00	Lebanon	1	0.00	Samoa	1	0.00	Zambia	11	0.50
Dominica	1	0.00	Lesotho	1	0.00	San Marino	1	0.00	Zimbabwe	10	0.59

Notes: All numbers refer to the Gini coefficient of ethnic inequality computed with population data from GPW ($\text{Gini}^e_{\text{GPW}}$). Due to differences in the population data, there are slight deviations between the number of ethnic groups used for the computation of $\text{Gini}^e_{\text{GPW}}$ and those employed to obtain $\text{Gini}^e_{\text{GHS}}$. Ethnic Inequality and the number of ethnicities are from the most recent year in our our dataset (2013). The number of ethnic groups

Table C-3 LIST OF COUNTRIES, NUMBER OF ETHNIC GROUPS (E), AND GINI INDICES OF ETHNIC INEQUALITY, WEIGHTED MEASURES, GINI(W)

Country	E	Gini	Country	E	Gini	Country	E	Gini	Country	E	Gini
Afghan.	22	0.25	Dom. Rep.	1	0.00	Liberia	9	0.43	Sao Tome	1	0.00
Albania	5	0.01	Ecuador	6	0.06	Libya	4	0.00	Saudi Arabia	2	0.00
Algeria	8	0.03	Egypt	4	0.00	Liechtenstein	1	0.00	Senegal	11	0.22
Andorra	1	0.00	El Salvador	4	0.01	Lithuania	5	0.02	Serbia	11	0.04
Angola	13	0.25	Eq. Guinea	3	0.25	Luxembourg	1	0.00	Seychelles	1	0.00
Antigua	1	0.00	Eritrea	10	0.31	Macedonia	5	0.04	Sierra Leone	6	0.23
Argentina	12	0.07	Estonia	2	0.07	Madagascar	1	0.00	Singapore	1	0.00
Armenia	7	0.06	Ethiopia	17	0.25	Malawi	5	0.18	Slovakia	4	0.02
Australia	3	0.03	Fiji	2	0.32	Malaysia	20	0.17	Slovenia	3	0.02
Austria	4	0.00	Finland	4	0.02	Mali	10	0.32	Solomon Is.	4	0.05
Azerbaijan	15	0.04	France	8	0.01	Malta	1	0.00	Somalia	4	0.02
Bahamas	1	0.00	Gabon	7	0.29	Mauritania	4	0.14	South Africa	13	0.16
Bahrain	1	0.00	Gambia	3	0.11	Mauritius	1	0.00	South Korea	1	0.00
Bangladesh	3	0.01	Georgia	15	0.09	Mexico	40	0.04	South Sudan	19	0.52
Belarus	5	0.01	Germany	4	0.00	Micronesia	2	0.12	Spain	4	0.04
Belgium	3	0.03	Ghana	12	0.20	Moldova	5	0.03	Sri Lanka	3	0.01
Belize	4	0.05	Greece	5	0.01	Monaco	1	0.00	St. Lucia	1	0.00
Benin	9	0.26	Grenada	1	0.00	Mongolia	15	0.06	St. Vincen	1	0.00
Bhutan	9	0.20	Guatemala	17	0.17	Montenegro	5	0.04	Sudan	19	0.12
Bolivia	16	0.21	Guinea	10	0.40	Morocco	7	0.05	Suriname	5	0.11
Bosnia	4	0.05	Guinea-Bis.	9	0.49	Mozambique	9	0.39	Swaziland	3	0.02
Botswana	6	0.12	Guyana	5	0.12	Namibia	8	0.34	Sweden	3	0.01
Brazil	50	0.03	Haiti	1	0.00	Nauru	1	0.00	Switzerland	4	0.06
Brunei	5	0.03	Honduras	7	0.03	Nepal	16	0.30	Syria	7	0.05
Bulgaria	4	0.01	Hungary	7	0.01	Netherlands	2	0.00	Taiwan	2	0.06
Burkina Faso	15	0.33	Iceland	1	0.00	New Zealand	2	0.00	Tajikistan	15	0.05
Myanmar	20	0.07	India	58	0.28	Nicaragua	7	0.02	Tanzania	30	0.50
Burundi	2	0.11	Indonesia	92	0.14	Niger	11	0.38	Thailand	18	0.14
Cambodia	12	0.26	Iran	27	0.10	Nigeria	28	0.30	Togo	11	0.39
Cameroon	20	0.47	Iraq	8	0.05	Norway	3	0.00	Tonga	1	0.00
Canada	20	0.07	Ireland	1	0.00	Oman	2	0.05	Trin. & Tob.	3	0.14
Cape Verde	1	0.00	Israel	3	0.04	Pakistan	16	0.09	Tunisia	3	0.01
Cen. Afr. Rep.	11	0.29	Italy	8	0.01	Palestina	2	0.08	Turkey	10	0.02
Chad	17	0.44	Ivory Coast	12	0.23	Panama	8	0.08	Turkmenist.	6	0.03
Chile	8	0.01	Jamaica	1	0.00	P.-N. Guinea	6	0.09	Uganda	14	0.61
China	57	0.06	Japan	2	0.00	Paraguay	9	0.02	Ukraine	12	0.04
Colombia	17	0.04	Jordan	2	0.05	Peru	14	0.11	UAE	2	0.21
Comoros	1	0.00	Kazakhstan	17	0.09	Philippines	35	0.20	UK	6	0.05
Costa Rica	8	0.02	Kenya	16	0.45	Poland	2	0.00	USA	28	0.01
Croatia	7	0.01	North Korea	1	0.00	Portugal	1	0.00	Uruguay	3	0.04
Cuba	1	0.00	Kosovo	4	0.00	Qatar	1	0.00	Uzbekistan	11	0.01
Cyprus	2	0.06	Kuwait	1	0.00	Rep. Congo	10	0.25	Vanuatu	2	0.08
Czech Rep.	3	0.01	Kyrgyzstan	9	0.09	Romania	11	0.02	Venezuela	9	0.01
Dem. Congo	31	0.58	Laos	19	0.31	Russia	82	0.11	Vietnam	35	0.15
Denmark	1	0.00	Latvia	7	0.03	Rwanda	2	0.03	Yemen	2	0.18
Djibouti	1	0.00	Lebanon	1	0.00	Samoa	1	0.00	Zambia	11	0.29
Dominica	1	0.00	Lesotho	1	0.00	San Marino	1	0.00	Zimbabwe	10	0.14

Notes: All numbers refer to the Gini coefficient of ethnic inequality computed with population data from GPW ($\text{Gini}^e_{\text{GPW}}$). Due to differences in the population data, there are slight deviations between the number of ethnic groups used for the computation of $\text{Gini}^e_{\text{GPW}}$ and those employed to obtain $\text{Gini}^e_{\text{GHS}}$. Ethnic Inequality and the number of ethnicities are from the most recent year in our our dataset (2013). The number of ethnic groups

Table C-4 ETHNIC INEQUALITY AND ECONOMIC GROWTH—DYNAMIC PANEL DATA ESTIMATES, ALTERNATIVE ESTIMATION STRATEGIES

Dependent variable: Real per capita GDP, $\log(\text{GDP}^{pc})$	Within Group		Bruno (2005a, 2005b)		Han and Phillips (2010)		Difference GMM		Nonparametric	
	(1) Gini(NW)	(2) Gini(W)	(3) Gini(NW)	(4) Gini(W)	(5) Gini(NW)	(6) Gini(W)	(7) Gini(NW)	(8) Gini(W)	(9) Gini(NW)	(10) Gini(W)
Ethnic Inequality	-0.096***	-0.175**	-0.095***	-0.104***	-0.513***	-0.214***	-0.402***	-0.316*	-0.009**	-0.084***
	(0.027)	(0.068)	(0.021)	(0.031)	(0.043)	(0.008)	(0.145)	(0.188)	(0.003)	(0.002)
Log GDP^{pc} $(t-1)$	1.109***	1.104***	0.941***	0.941***	1.720***	1.674***	1.038***	0.882***	0.195***	1.094***
	(0.051)	(0.052)	(0.008)	(0.008)	(0.071)	(0.084)	(0.088)	(0.083)	(0.0700)	(0.0617)
Log GDP^{pc} $(t-2)$	-0.156***	-0.154***					-0.241***	-0.199***	-0.006	-0.175***
	(0.037)	(0.037)					(0.081)	(0.068)	(0.0548)	(0.0440)
Log GDP^{pc} $(t-3)$	0.029	0.031					0.057	0.068	0.059***	0.0541
	(0.055)	(0.055)					(0.063)	(0.048)	(0.0199)	(0.0533)
Log GDP^{pc} $(t-4)$	-0.092***	-0.095***					-0.055***	-0.045*	-0.022	-0.166***
	(0.018)	(0.019)					(0.020)	(0.022)	(0.036)	(0.0190)
Observations	3,615	3,615	3,656	3,656	3,656	3,656	3,448	3,448	3,615	3,615
Countries	167	167	167	167	167	167	167	167	167	167
R-Squared	0.998	0.998	–	–	0.999	0.999	–	–	–	–
F/χ^2 Stat	1193	1186	–	–	364.8	313.3	7976	4534	–	–
F/χ^2 p-val	0.000	0.000	–	–	0.000	0.000	0.000	0.000	–	–
First-stage results	–	–	–	–	–	–	–	–	–	–
Hansen p-val	–	–	–	–	–	–	0.507	0.338	–	–
AR(1) p-val	–	–	–	–	–	–	0.000	0.000	–	–
AR(2) p-val	–	–	–	–	–	–	0.217	0.279	–	–
Country Fixed Effects	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
Period Fixed Effects	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes

Notes: The dependent variable is the log of real per capita GDP, measured using data from the Penn World Tables Version 9.1. Ethnic inequality is measured as described in Section (2) using differences in nighttime lights across ethnic homelands. The table is based on weighted ethnic inequality computed using corrected light data, Gini(W). All specifications include country fixed effects and year fixed effects. Columns (1)–(2) report our baseline Within-Group estimates as a benchmark. Columns (3)–(4) uses a bias-corrected version of the LSDV estimator introduced by Bruno (2005a,b). The estimator uses 100 bootstrapping iterations to obtain robust standard errors and exploits the Arellano and Bond (1991) estimator as initially consistent estimate. The Han and Phillips (2010) estimator reported in columns (5)–(6) is a procedure for dynamic panel data models with fixed effects and incidental trends. We implement the estimator with 100 iterations. Columns (5)–(6) present two-step different GMM estimates based on the technique proposed by Arellano and Bond (1991). Each regressor is treated as endogenous, while period fixed effects are specified to be predetermined. The instrument matrix uses two lags in both the levels and the difference equation, Windmeijer-corrected (robust) standard errors in parentheses. AR(1) p-val and AR(2) p-val denote the p-value of the respective AR(n) test, Hansen p-val gives the p-value of Hansen's J-Test for over-identifying restrictions. F/ξ^2 Stat and F/ξ^2 p-val denote the results from the F test (columns 1–6) and the χ^2 test (columns 7–8) for joint significance of the regressors. The construction of the nonparametric estimator follows a tow-step procedure that is decribed in detail in Apendix A.3. The reported effects are averages of derivatives of log per capita GDP with regard to ethnic inequality. Standard errors are obtained based on 100 bootstrapping iterations. $*p < .10$, $**p < .05$, $***p < .01$

Table C-5 ETHNIC INEQUALITY AND ECONOMIC GROWTH—EFFECTS OF ALTERNATIVE CONSTRUCTION PROCESSES OF ETHNIC INEQUALITY I: EXCLUDING SMALL GROUPS

Dependent variable: Real per capita GDP, log(GDP^{pc})				
	Baseline (1)	Excl. groups $\leq 2,000$ (2)	Excl. groups $\leq 0.1\%$ (3)	Excl. groups $\leq 1\%$ (4)
Ethnic Inequality	-0.0957***	-0.0652**	-0.0739***	-0.0589**
	(0.0273)	(0.0255)	(0.0277)	(0.0297)
Log GDP^{pc} $(t-1)$	1.109***	1.111***	1.111***	1.112***
	(0.0513)	(0.0514)	(0.0515)	(0.0516)
Log GDP^{pc} $(t-2)$	-0.156***	-0.156***	-0.155***	-0.155***
	(0.0373)	(0.0373)	(0.0373)	(0.0373)
Log GDP^{pc} $(t-3)$	0.0292	0.0293	0.0284	0.0285
	(0.0546)	(0.0546)	(0.0546)	(0.0547)
Log GDP^{pc} $(t-4)$	-0.0920***	-0.0921***	-0.0913***	-0.0913***
	(0.0184)	(0.0184)	(0.0183)	(0.0185)
Observations	3615	3615	3615	3615
Countries	167	167	167	167
R-Squared	0.954	0.953	0.954	0.954
F Stat	1193.0	1157.2	1258.7	1249.4
Country Fixed Effects	yes	yes	yes	yes
Period Fixed Effects	yes	yes	yes	yes
Equality	–	0.266	0.427	0.180

Notes: Cluster robust standard errors are reported in parentheses. The dependent variable is the log of real per capita GDP, measured using data from the Penn World Tables Version 9.1. Ethnic inequality is measured as described in Section (2) using differences in nighttime lights across ethnic homelands. The table is based on variations of the non-weighted ethnic inequality measure computed using corrected light data—Gini(NW)—that exclude small groups to a different extent. Column "Excl. groups $\leq$ 2,000" excludes all groups with 2,000 member or less , "Excl. groups $\leq$ 0.1%" excludes all group accounting for a fraction of 0.1% of population or less, and column "Excl. groups $\leq$ 1%" excludes all groups accounting for a fraction of 1% of total population. All specifications include country fixed effects and year fixed effects. The rest of the construction process is identical to our baseline version of ethnic inequality. "Equality" reports the p-value of a Wald test that compares the parameter estimates with the baseline estimate in column (1).

*** Significant at the 1 percent level,
** Significant at the 5 percent level,
* Significant at the 10 percent level

Table C-6 ETHNIC INEQUALITY AND ECONOMIC GROWTH—EFFECTS OF ALTERNATIVE CONSTRUCTION PROCESSES OF ETHNIC INEQUALITY II: USING GeoEPR TO MAP ETHNIC HOMELANDS

Dependent variable: Real per capita GDP, log(GDP^{pc})

	Non-Weighted Ethnic Inequality			**Weighted Ethnic Inequality**		
	Baseline GREG (1)	Current Borders GeoEPR (2)	1969 Borders GeoEPR (3)	Baseline GREG (4)	Current Borders GeoEPR (5)	1969 Borders GeoEPR (6)
Ethnic Inequality	-0.0957***	-0.0634**	-0.0837**	-0.175**	-0.201***	-0.204***
	(0.0273)	(0.0310)	(0.0367)	(0.0681)	(0.0717)	(0.0726)
Log GDP^{pc} $(t-1)$	1.109***	1.111***	1.109***	1.104***	1.099***	1.098***
	(0.0513)	(0.0524)	(0.0524)	(0.0516)	(0.0528)	(0.0530)
Log GDP^{pc} $(t-2)$	-0.156***	-0.154***	-0.154***	-0.154***	-0.147***	-0.148***
	(0.0373)	(0.0375)	(0.0374)	(0.0371)	(0.0358)	(0.0358)
Log GDP^{pc} $(t-3)$	0.0292	0.0336	0.0336	0.0305	0.0312	0.0319
	(0.0546)	(0.0546)	(0.0544)	(0.0546)	(0.0563)	(0.0562)
Log GDP^{pc} $(t-4)$	-0.0920***	-0.0976***	-0.0979***	-0.0948***	-0.0977***	-0.0969***
	(0.0184)	(0.0173)	(0.0173)	(0.0188)	(0.0183)	(0.0182)
Observations	3615	3559	3559	3615	3507	3507
Countries	167	165	165	167	162	162
R-Squared	0.954	0.954	0.954	0.954	0.954	0.954
F Stat	1193.0	1175.6	1196.3	1186.3	1265.4	1307.3
Country Fixed Effects	yes	yes	yes	yes	yes	yes
Period Fixed Effects	yes	yes	yes	yes	yes	yes
Equality	–	0.240	0.662	–	0.707	0.674

Notes: Cluster robust standard errors are reported in parentheses. The dependent variable is the log of real per capita GDP, measured using data from the Penn World Tables Version 9.1. Ethnic inequality is measured as described in Section (2) using differences in nighttime lights across ethnic homelands. The table uses an alternative map of ethnic homelands from the GeoEPR project (Vogt et al., 2015). The rest of the construction process is identical to our baseline version of ethnic inequality. We construct alternative measures of ethnic inequality both without weighting for population size of ethnic groups (columns 2 and 3) and with population weighting (columns 5 and 6). Columns (1) and (4) report our baseline variants for comparison. Column "Current Borders" shows the construction of ethnic inequality using current borders as they appear in GeoEPR, while "1969 Borders" shows the construction of ethnic inequality when we back-reference the borders to fit the political situation of 1969. All indices are based on corrected nighttime light data. All specifications include country fixed effects and year fixed effects. "Equality" reports the p-value of a Wald test that compares the parameter estimates with our corresponding baseline variant of ethnic inequality.

*** Significant at the 1 percent level,
** Significant at the 5 percent level,
* Significant at the 10 percent level

Table C-7 ETHNIC INEQUALITY AND ECONOMIC GROWTH—EFFECTS OF ALTERNATIVE CONSTRUCTION PROCESSES OF ETHNIC INEQUALITY III: EXCLUDING LARGE URBAN AREAS

Dependent variable: Real per capita GDP, log(GDP^{pc})

	Non-Weighted Ethnic Inequality		**Weighted Ethnic Inequality**	
	Baseline (1)	Exclude Urban Areas (2)	Baseline (3)	Exclude Urban Areas (4)
Ethnic Inequality	-0.0957***	-0.0804***	-0.175**	-0.128**
	(0.0273)	(0.0253)	(0.0681)	(0.0611)
Log GDP^{pc} $(t-1)$	1.109***	1.103***	1.104***	1.098***
	(0.0513)	(0.0500)	(0.0516)	(0.0505)
Log GDP^{pc} $(t-2)$	-0.156***	-0.143***	-0.154***	-0.141***
	(0.0373)	(0.0403)	(0.0371)	(0.0401)
Log GDP^{pc} $(t-3)$	0.0292	0.0128	0.0305	0.0148
	(0.0546)	(0.0650)	(0.0546)	(0.0650)
Log GDP^{pc} $(t-4)$	-0.0920***	-0.0794***	-0.0948***	-0.0811***
	(0.0184)	(0.0237)	(0.0188)	(0.0239)
Observations	3615	3592	3615	3592
Countries	167	166	167	166
R-Squared	0.954	0.954	0.954	0.954
F Stat	1193.0	1149.7	1186.3	1198.1
Country Fixed Effects	yes	yes	yes	yes
Period Fixed Effects	yes	yes	yes	yes
Equality	–	0.577	–	0.488

Notes: Cluster robust standard errors are reported in parentheses. The dependent variable is the log of real per capita GDP, measured using data from the Penn World Tables Version 9.1. Ethnic inequality is measured as described in Section (2) using differences in nighttime lights across ethnic homelands. The table uses a variant of our ethnic inequality measure where we exclude large urban areas with a population size of 750,000 inhabitants or larger. The rest of the construction process is identical to our baseline version of ethnic inequality. We construct alternative measures of ethnic inequality both without weighting for population size of ethnic groups (column 2) and with population weighting (columns 4). Columns (1) and (3) report our baseline variants for comparison. All specifications include country fixed effects and year fixed effects. "Equality" reports the p-value of a Wald test that compares the parameter estimates with our corresponding baseline variant of ethnic inequality.

*** Significant at the 1 percent level,
** Significant at the 5 percent level,
* Significant at the 10 percent level

Table C-8 ETHNIC INEQUALITY AND ECONOMIC GROWTH—ACCOUNTING FOR CONFOUNDING FACTORS: NON-WEIGHTED GINI INDEX OF ETHNIC INEQUALITY, GINI(NW)

Dependent variable: Real per capita GDP, log(GDP^{pc})							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Ethnic Inequality	-0.0918***	-0.0954***	-0.0928***	-0.0973***	-0.0961***	-0.0939***	-0.0689**
	(0.0313)	(0.0351)	(0.0281)	(0.0283)	(0.0288)	(0.0270)	(0.0338)
Log GDP^{pc} $(t-1)$	1.084***	1.122***	1.104***	1.110***	1.115***	1.106***	1.041***
	(0.0593)	(0.0729)	(0.0532)	(0.0521)	(0.0471)	(0.0536)	(0.0760)
Log GDP^{pc} $(t-2)$	-0.156***	-0.233***	-0.160***	-0.153***	-0.147***	-0.153***	-0.207***
	(0.0413)	(0.0653)	(0.0383)	(0.0376)	(0.0559)	(0.0395)	(0.0685)
Log GDP^{pc} $(t-3)$	0.0500	0.0954	0.0350	0.0271	0.00547	0.0365	0.110*
	(0.0607)	(0.0743)	(0.0541)	(0.0557)	(0.0459)	(0.0530)	(0.0629)
Log GDP^{pc} $(t-4)$	-0.0970***	-0.0859***	-0.0944***	-0.0936***	-0.0715***	-0.0979***	-0.0791***
	(0.0171)	(0.0309)	(0.0171)	(0.0186)	(0.0199)	(0.0168)	(0.0253)
Human Capital	0.0141						0.0349
	(0.0227)						(0.0372)
Investment		0.00184					0.00240
		(0.00144)					(0.00179)
Globalization			0.00163***				0.00188*
			(0.000566)				(0.00104)
Fertility				0.00236			-0.00655
				(0.00428)			(0.00918)
Natural Resources					0.000431		-0.0000263
					(0.000442)		(0.00108)
Political Instability						-0.0213**	0.00578
						(0.00966)	(0.00799)
Observations	3027	1990	3551	3507	3472	3571	1795
Countries	139	125	164	163	163	165	111
R-Squared	0.947	0.966	0.954	0.953	0.959	0.954	0.964
F Stat	946.9	1358.0	1063.5	1076.2	1392.4	1148.3	1307.0
Country Fixed Effects	yes	yes	yes	yes	yes	yes	yes
Period Fixed Effects	yes	yes	yes	yes	yes	yes	yes

Notes: Cluster robust standard errors are reported in parentheses. The dependent variable is the log of real per capita GDP, measured using data from the Penn World Tables Version 9.1. Ethnic inequality is measured as described in Section (2) using differences in nighttime lights across ethnic homelands. The table is based on non-weighted ethnic inequality computed using corrected light data, Gini(NW). All specifications include country fixed effects and year fixed effects. Data on the control variables comes from the following sources: the index of human capital is from Penn World Tables, version 9.1; investment, fertility, and natural resource rents are taken from the World Development Indicators of World Bank (2020), Globalization is measured by the KOF Globalization Index of Gygli et al. (2019), and political instability is measured by Coups d'État compiled by Bjørnskov and Rode (2020).

*** Significant at the 1 percent level,
** Significant at the 5 percent level,
* Significant at the 10 percent level

Table C-9 ETHNIC INEQUALITY AND ECONOMIC GROWTH—ACCOUNTING FOR CONFOUNDING FACTORS: WEIGHTED GINI INDEX OF ETHNIC INEQUALITY, GINI(W)

Dependent variable: Real per capita GDP, log(GDP^{pc})							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Ethnic Inequality	-0.127**	-0.161**	-0.191**	-0.182**	-0.155***	-0.171**	-0.207**
	(0.0607)	(0.0768)	(0.0750)	(0.0718)	(0.0552)	(0.0688)	(0.0841)
Log GDP^{pc} $(t-1)$	1.085***	1.125***	1.096***	1.104***	1.110***	1.101***	1.038***
	(0.0592)	(0.0732)	(0.0532)	(0.0524)	(0.0480)	(0.0537)	(0.0758)
Log GDP^{pc} $(t-2)$	-0.156***	-0.233***	-0.157***	-0.150***	-0.144**	-0.150***	-0.208***
	(0.0413)	(0.0652)	(0.0380)	(0.0373)	(0.0557)	(0.0392)	(0.0680)
Log GDP^{pc} $(t-3)$	0.0502	0.0946	0.0362	0.0284	0.00592	0.0376	0.112*
	(0.0612)	(0.0748)	(0.0542)	(0.0558)	(0.0462)	(0.0531)	(0.0624)
Log GDP^{pc} $(t-4)$	-0.0962***	-0.0867***	-0.0969***	-0.0968***	-0.0744***	-0.101***	-0.0774***
	(0.0173)	(0.0312)	(0.0176)	(0.0190)	(0.0199)	(0.0173)	(0.0251)
Human Capital	0.0144						0.0387
	(0.0229)						(0.0373)
Investment		0.00182					0.00255
		(0.00148)					(0.00181)
Globalization			0.00187***				0.00192*
			(0.000559)				(0.00104)
Fertility				0.00234			-0.00582
				(0.00457)			(0.00887)
Natural Resources					0.000446		-0.00000745
					(0.000426)		(0.00106)
Political Instability						-0.0213**	0.00745
						(0.00968)	(0.00790)
Observations	3027	1990	3551	3507	3472	3571	1795
Countries	139	125	164	163	163	165	111
R-Squared	0.947	0.966	0.954	0.953	0.959	0.954	0.964
F Stat	983.9	1434.4	1028.8	1068.4	1423.0	1135.0	1279.6
Country Fixed Effects	yes	yes	yes	yes	yes	yes	yes
Period Fixed Effects	yes	yes	yes	yes	yes	yes	yes

Notes: Robust standard errors are reported in parentheses. The dependent variable is the log of real per capita GDP, measured using data from the Penn World Tables Version 9.1. Ethnic inequality is measured as described in Section (2) using differences in nighttime lights across ethnic homelands. The table is based on weighted ethnic inequality computed using corrected light data, Gini(W). All specifications include country fixed effects and year fixed effects. Data on the control variables comes from the following sources: the index of human capital is from Penn World Tables, version 9.1; investment, fertility, and natural resource rents are taken from the World Development Indicators of World Bank (2020), Globalization is measured by the KOF Globalization Index of Gygli et al. (2019), and political instability is measured by Coups d'État compiled by Bjørnskov and Rode (2020).

*** Significant at the 1 percent level,
** Significant at the 5 percent level,
* Significant at the 10 percent level

Table C-10 ETHNIC INEQUALITY AND ECONOMIC GROWTH—THE ROLE OF SPATIAL INEQUALITY AND POPULATION-RELATED INEQUALITY

Dependent variable: Real per capita GDP, log(GDP^{pc})

	Baseline	Inequality Across Sub-National Units				Population-related Inequality		
		Spatial Inequality	Gini(NW)	Gini(NW)	Gini(W)	Population size	Population Inequality	Ethnic Fractionalization
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Ethnic Inequality	-0.0957***		-0.0541**	-0.0495*	-0.123*	-0.0924***	-0.0947***	-0.0960***
	(0.0273)		(0.0271)	(0.0270)	(0.0704)	(0.0271)	(0.0271)	(0.0274)
Log GDP^{pc} $(t-1)$	1.109***	1.106***	1.105***	1.101***	1.097***	1.108***	1.109***	1.112***
	(0.0513)	(0.0521)	(0.0521)	(0.0520)	(0.0523)	(0.0513)	(0.0513)	(0.0526)
Log GDP^{pc} $(t-2)$	-0.156***	-0.154***	-0.155***	-0.150***	-0.148***	-0.155***	-0.156***	-0.158***
	(0.0373)	(0.0372)	(0.0374)	(0.0371)	(0.0372)	(0.0372)	(0.0373)	(0.0386)
Log GDP^{pc} $(t-3)$	0.0292	0.0344	0.0348	0.0342	0.0354	0.0292	0.0291	0.0356
	(0.0546)	(0.0551)	(0.0549)	(0.0550)	(0.0549)	(0.0544)	(0.0546)	(0.0545)
Log GDP^{pc} $(t-4)$	-0.0920***	-0.0951***	-0.0956***	-0.0983***	-0.101***	-0.0991***	-0.0921***	-0.0982***
	(0.0184)	(0.0177)	(0.0175)	(0.0174)	(0.0176)	(0.0184)	(0.0184)	(0.0170)
Spatial Inequality		-0.120***	-0.0989**	-0.103**	-0.0852**			
		(0.0450)	(0.0478)	(0.0489)	(0.0405)			
Population Size								
Ethnic Inequality in Population						2.38**	-0.116	
						(0.976)	(0.273)	
Ethnic Fractionalization								0.113
								(0.0904)
Observations	3615	3581	3581	3491	3469	3615	3615	3581
Countries	167	166	166	162	161	167	167	166
R-Squared	0.954	0.954	0.954	0.954	0.954	0.954	0.954	0.954
F Stat	1193.0	1350.0	1297.4	.	.	1147.6	.	1149.1
Country Fixed Effects	yes	yes	yes	yes	yes	yes	yes	yes
Period Fixed Effects	yes	yes	yes	yes	yes	yes	yes	yes
Population Controls	no	no	no	yes	yes	no	no	no
Land Area Controls	no	no	no	yes	yes	no	no	no

Notes: Robust standard errors are reported in parentheses. The dependent variable is the log of real per capita GDP, measured using data from the Penn World Tables Version 9.1. Ethnic inequality is measured as described in Section (2) using differences in nighttime lights across ethnic homelands. All specifications include country fixed effects and year fixed effects. Spatial inequality is computed by measuring corrected nighttime lights (calibrated and top-coding adjusted) at the first administrative level and computing inequality measures across ADM1 regions following the construction of the Gini index of ethnic inequality. Population size uses our population measures that combines data of GPW and GHS. Ethnic inequality in population measures inequality in population across ethnic homelands. The construction process of our measure of ethnic fractionalization is described in Appendix A.7. "Population Controls" and "Land Area Controls" contain the number of population and a country's total land area, which is the surface area excluding area under inland water bodies, national claims to continental shelf, and exclusive economic zones.

*** Significant at the 1 percent level,
** Significant at the 5 percent level,
* Significant at the 10 percent level

Table C-11 ETHNIC INEQUALITY AND ECONOMIC GROWTH—EFFECTS FOR GEOGRAPHIC UNITS

Dependent variable: Real per capita GDP, log(GDP^{pc})					
	Africa (1)	South America (2)	Central & North America (3)	Europe (4)	Asia (5)
	Panel A: Non-Weighted Ethnic Inequality—Gini(NW)				
Ethnic Inequality	-0.266***	-0.0413	-0.0345*	-0.0247	-0.172***
	(0.0569)	(0.0702)	(0.0181)	(0.0416)	(0.0636)
Log GDP^{pc} $(t-1)$	1.119***	1.258***	1.172***	1.302***	1.129***
	(0.0640)	(0.0566)	(0.0784)	(0.0933)	(0.106)
Log GDP^{pc} $(t-2)$	-0.0738	-0.356***	-0.148	-0.305	-0.214***
	(0.0512)	(0.112)	(0.116)	(0.198)	(0.0738)
Log GDP^{pc} $(t-3)$	-0.0706	0.185**	-0.122	-0.0134	0.144***
	(0.0748)	(0.0727)	(0.0729)	(0.142)	(0.0435)
Log GDP^{pc} $(t-4)$	-0.0633**	-0.108**	0.0561	-0.0501	-0.113***
	(0.0272)	(0.0364)	(0.0426)	(0.0362)	(0.0237)
Observations	1100	242	440	838	907
Countries	50	11	20	40	42
R-Squared	0.931	0.942	0.962	0.971	0.956
F Stat	3380.7	2210.8	2110.0	3202.1	4015.7
	Panel B: Weighted Ethnic Inequality—Gini(W)				
Ethnic Inequality	-0.285***	-0.174	-0.113*	0.419**	-0.154**
	(0.0850)	(0.110)	(0.0654)	(0.172)	(0.0733)
Log GDP^{pc} $(t-1)$	1.114***	1.241***	1.169***	1.309***	1.138***
	(0.0642)	(0.0609)	(0.0771)	(0.0960)	(0.105)
Log GDP^{pc} $(t-2)$	-0.0714	-0.347**	-0.144	-0.309	-0.213***
	(0.0498)	(0.112)	(0.115)	(0.199)	(0.0750)
Log GDP^{pc} $(t-3)$	-0.0671	0.187**	-0.121	-0.0133	0.146***
	(0.0782)	(0.0774)	(0.0728)	(0.143)	(0.0451)
Log GDP^{pc} $(t-4)$	-0.0718**	-0.105**	0.0580	-0.0496	-0.115***
	(0.0308)	(0.0335)	(0.0424)	(0.0367)	(0.0229)
Observations	1100	242	440	838	907
Countries	49	11	20	40	42
R-Squared	0.928	0.943	0.962	0.972	0.956
F Stat	2949.8	3860.0	2759.1	4345.3	2612.5

Notes: Robust standard errors are reported in parentheses. The dependent variable is the log of real per capita GDP, measured using data from the Penn World Tables Version 9.1. Ethnic inequality is measured as described in Section (2) using differences in nighttime lights across ethnic homelands. The ethnic inequality measures used in the table are: our version of ethnic inequality using corrected light data (Gini(NW) in Panel A) and our version of ethnic inequality using corrected light data and weights for the size of ethnic groups (Gini(W) in Panel B). All specifications include country fixed effects. Regressions for Oceania are not reported because of the limited number of observations.

*** Significant at the 1 percent level,
** Significant at the 5 percent level,
* Significant at the 10 percent level

Table C-12 ETHNIC INEQUALITY AND ECONOMIC GROWTH—SUB-NATIONAL ESTIMATES, AFRICAN REGIONS, WEIGHTED MEASURE OF SUB-NATIONAL ETHNIC INEQUALITY, 1992–2012

Dependent variable: Real per capita GRP, log(GRP^{pc})

	Benchmark		**Country-Year FE**		**Spatial Correlation**	
	FE-OLS (1)	2SLS (2)	FE-OLS (3)	2SLS (4)	FE-OLS (5)	2SLS (6)
	Panel A: Regression results (second stage)					
Ethnic inequality	-0.0386***	-0.0650***	-0.00700***	-0.0179***	-0.00701***	-0.0178***
	(0.00619)	(0.0126)	(0.00237)	(0.00450)	(0.00238)	(0.00451)
log(GRP^{pc})$(t-1)$	0.747***	0.743***	0.711***	0.709***	0.711***	0.709***
	(0.0452)	(0.0448)	(0.0266)	(0.0264)	(0.0266)	(0.0264)
log(GRP^{pc})$(t-2)$	0.215***	0.214***	0.172***	0.171***	0.172***	0.171***
	(0.0512)	(0.0509)	(0.0225)	(0.0224)	(0.0225)	(0.0224)
log(GRP^{pc})$(t-3)$	-0.00464	-0.00394	0.0608**	0.0611**	0.0608**	0.0611**
	(0.0177)	(0.0177)	(0.0286)	(0.0285)	(0.0286)	(0.0285)
log(GRP^{pc})$(t-4)$	-0.0321**	-0.0334***	0.0458**	0.0460**	0.0455**	0.0458**
	(0.0129)	(0.0127)	(0.0207)	(0.0207)	(0.0207)	(0.0207)
	Panel B: First-stage regression results					
Spatial Instrument	–	0.534***	–	0.522***	–	0.522***
		(0.0483)		(0.0508)		(0.0510)
Observations	9,280	9,280	9,280	9,280	9,280	9,280
Sub-national Units	589	589	589	589	589	589
R-Squared	0.907	0.907	0.985	0.985	0.985	0.985
F Stat (second)	32134	3308	104601	104071	88827	88182
K-P F-Stat (first)	–	122.61	–	105.27	–	104.87
S-Y 10% max IV size	–	16.38	–	16.38	–	16.38
S-W p-val	–	0.000	–	0.000	–	0.000
Country Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Period Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Country-Year Fixed Effects	No	No	Yes	Yes	Yes	Yes
Spatial Correlation	No	No	No	No	Yes	Yes

Notes: Cluster robust standard errors (on the ADM1 level) are reported in parentheses. The dependent variable is the log of real per capita GRP, measured using data from Leßmann and Seidel (2017). Ethnic inequality is measured as described in Section (2) using differences in nighttime lights across ethnic homelands. The table presents estimates from three models, each estimated with the traditional within group estimator (columns labeled "FE-OLS") and with 2SLS using our spatial instrumental variable. The first model ("Benchmark") replicates the specification of the country-level dynamic panel data model of Section (3.2), the second specification ("Country-Year FE") accounts for time-varying unobservables on the country level by including country-year fixed effects. The third specification ("Spatial Correlation") accounts for spatial correlation between the GRP of sub-national units and a the average of GRP in other sub-national units of the same country, weighted by the inverse of the distance between sub-national units. The row labeled "K-P F-Stat (first)" reports the F-statistic of the Kleibergen-Paap rk Wald test, which is a robust test for weak identification in case the errors are not i.i.d. We also report Stock-Yogo thresholds for the Kleibergen-Paap weak identification test for a demanding critical value of 10% max IV size (labeled "S-Y 10% max IV size"). The row labeled "S-W p-val" presents p-values of the Stock-Wright LM test, presenting weak-instrument-robust inference. The null of this test is that the endogenous regressor is equal to zero. The test is robust to the presence of weak instruments.

*** Significant at the 1 percent level,
** Significant at the 5 percent level,
* Significant at the 10 percent level

Table C-13 ETHNIC INEQUALITY AND ECONOMIC GROWTH—SUB-NATIONAL ESTIMATES, AFRICAN REGIONS, EXCLUDING SUB-NATIONAL REGIONS WITH BORDER-CHANGES, 1992–2012

Dependent variable: Real per capita GRP, $\log(\text{GRP}^{pc})$						
	Benchmark		**Country-Year FE**		**Spatial Correlation**	
	FE-OLS (1)	2SLS (2)	FE-OLS (3)	2SLS (4)	FE-OLS (5)	2SLS (6)
	Panel A: Regression results (second stage)					
Ethnic inequality	-0.0377***	-0.0502***	-0.0060***	-0.0070***	-0.0060***	-0.0069***
	(0.0057)	(0.0086)	(0.0017)	(0.0024)	(0.0017)	(0.0024)
$\log(\text{GRP}^{pc})(t-1)$	0.686***	0.683***	0.738***	0.738***	0.738***	0.738***
	(0.0478)	(0.0475)	(0.0281)	(0.0280)	(0.0281)	(0.0280)
$\log(\text{GRP}^{pc})(t-2)$	0.251***	0.250***	0.178***	0.178***	0.179***	0.178***
	(0.0559)	(0.0557)	(0.0256)	(0.0256)	(0.0256)	(0.0256)
$\log(\text{GRP}^{pc})(t-3)$	0.0111	0.0112	0.0191	0.0190	0.0191	0.0191
	(0.0201)	(0.0201)	(0.0360)	(0.0360)	(0.0360)	(0.0359)
$\log(\text{GRP}^{pc})(t-4)$	-0.0309**	-0.0320**	0.0540**	0.0541**	0.0537**	0.0537**
	(0.0146)	(0.0145)	(0.0262)	(0.0262)	(0.0262)	(0.0262)
	Panel B: First-stage regression results					
Spatial Instrument	–	0.968***	–	0.925***	–	0.925***
		(0.0488)		(0.0533)		(0.0533)
Observations	7,569	7,569	7,569	7,569	7,569	7,569
Sub-national Units	570	570	570	570	570	570
R-Squared	0.902	0.902	0.987	0.987	0.987	0.987
F Stat (second)	3837.5	3903.8	88012	88682	74488	75072
K-P F-Stat (first)	–	393.6	–	300.6	–	301.0
S-Y 10% max IV size	–	16.38	–	16.38	–	16.38
S-W p-val	–	0.000	–	0.000	–	0.000
Country Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Period Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Country-Year Fixed Effects	No	No	Yes	Yes	Yes	Yes
Spatial Correlation	No	No	No	No	Yes	Yes

Notes: Cluster robust standard errors (on the ADM1 level) are reported in parentheses. The dependent variable is the log of real per capita GRP, measured using data from Leßmann and Seidel (2017). The table reports estimates when we exclude sub-national regions with border changes. Ethnic inequality is measured as described in Section (2) using differences in nighttime lights across ethnic homelands. The table presents estimates from three models, each estimated with the traditional within group estimator (columns labeled "FE-OLS") and with 2SLS using our spatial instrumental variable. The first model ("Benchmark") replicates the specification of the country-level dynamic panel data model of Section (3.2), the second specification ("Country-Year FE") accounts for time-varying unobservables on the country level by including country-year fixed effects. The third specification ("Spatial Correlation") accounts for spatial correlation between the GRP of sub-national units and a the average of GRP in other sub-national units of the same country, weighted by the inverse of the distance between sub-national units. The row labeled "K-P F-Stat (first)" reports the F-statistic of the Kleibergen-Paap rk Wald test, which is a robust test for weak identification in case the errors are not i.i.d. We also report Stock-Yogo thresholds for the Kleibergen-Paap weak identification test for a demanding critical value of 10% max IV size (labeled "S-Y 10% max IV size"). The row labeled "S-W p-val" presents p-values of the Stock-Wright LM test, presenting weak-instrument-robust inference. The null of this test is that the endogenous regressor is equal to zero. The test is robust to the presence of weak instruments.

*** Significant at the 1 percent level,
** Significant at the 5 percent level,
* Significant at the 10 percent level

Table C-14 ETHNIC INEQUALITY AND ECONOMIC GROWTH—SUB-NATIONAL ESTIMATES, AFRICAN REGIONS, ALTERNATIVE SPECIFICATION OF THE INSTRUMENTAL VARIABLE, 1992–2012

Dependent variable: Real per capita GRP, log(GRP^{pc})						
	Benchmark		**Country-Year FE**		**Spatial Correlation**	
	FE-OLS (1)	2SLS (2)	FE-OLS (3)	2SLS (4)	FE-OLS (5)	2SLS (6)
	Panel A: Regression results (second stage)					
Ethnic inequality	-0.0354***	-0.0520***	-0.0062***	-0.0107***	-0.0063***	-0.0105***
	(0.0047)	(0.0071)	(0.0016)	(0.0022)	(0.0016)	(0.0022)
log(GRP^{pc})($t-1$)	0.741***	0.737***	0.710***	0.708***	0.710***	0.708***
	(0.0449)	(0.0446)	(0.0265)	(0.0264)	(0.0265)	(0.0264)
log(GRP^{pc})($t-2$)	0.216***	0.216***	0.172***	0.172***	0.173***	0.172***
	(0.0510)	(0.0507)	(0.0225)	(0.0224)	(0.0225)	(0.0224)
log(GRP^{pc})($t-3$)	-0.00446	-0.00383	0.0610**	0.0609**	0.0610**	0.0609**
	(0.0177)	(0.0176)	(0.0286)	(0.0285)	(0.0286)	(0.0285)
log(GRP^{pc})($t-4$)	-0.0341***	-0.0357***	0.0452**	0.0451**	0.0450**	0.0449**
	(0.0127)	(0.0126)	(0.0207)	(0.0206)	(0.0207)	(0.0206)
	Panel B: First-stage regression results					
Spatial Instrument	–	0.874***	–	0.857***	–	0.860***
		(0.0379)		(0.0421)		(0.0198)
Observations	9,280	9,280	9,280	9,280	9,280	9,280
Sub-national Units	589	589	589	589	589	589
R-Squared	0.908	0.907	0.985	0.985	0.985	0.985
F Stat (second)	4400	4412	107284	105746	91477	90255
K-P F-Stat (first)	–	530.0	–	412.5	–	423.5
S-Y 10% max IV size	–	16.38	–	16.38	–	16.38
S-W p-val	–	0.000	–	0.000	–	0.000
Country Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Period Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Country-Year Fixed Effects	No	No	Yes	Yes	Yes	Yes
Spatial Correlation	No	No	No	No	Yes	Yes

Notes: Cluster robust standard errors (on the ADM1 level) are reported in parentheses. The dependent variable is the log of real per capita GRP, measured using data from Leßmann and Seidel (2017). Ethnic inequality is measured as described in Section (2) using differences in nighttime lights across ethnic homelands. The table presents estimates from three models, each estimated with the traditional within group estimator (columns labeled "FE-OLS") and with 2SLS using an adjusted version of our spatial instrumental variable that only considers ethnic groups outside the home country of the sub-national regions for which the instrument is constructed. The first model ("Benchmark") replicates the specification of the country-level dynamic panel data model of Section (3.2), the second specification ("Country-Year FE") accounts for time-varying unobservables on the country level by including country-year fixed effects. The third specification ("Spatial Correlation") accounts for spatial correlation between the GRP of sub-national units and a the average of GRP in other sub-national units of the same country, weighted by the inverse of the distance between sub-national units. The row labeled "K-P F-Stat (first)" reports the F-statistic of the Kleibergen-Paap rk Wald test, which is a robust test for weak identification in case the errors are not i.i.d. We also report Stock-Yogo thresholds for the Kleibergen-Paap weak identification test for a demanding critical value of 10% max IV size (labeled "S-Y 10% max IV size"). The row labeled "S-W p-val" presents p-values of the Stock-Wright LM test, presenting weak-instrument-robust inference. The null of this test is that the endogenous regressor is equal to zero. The test is robust to the presence of weak instruments.

*** Significant at the 1 percent level,
** Significant at the 5 percent level,
* Significant at the 10 percent level

Table C-15 ETHNIC INEQUALITY AND ECONOMIC GROWTH—SUB-NATIONAL ESTIMATES, AFRICAN REGIONS, ALTERNATIVE CLUSTERING (COUNTRY-LEVEL), 1992–2012

Dependent variable: Real per capita GRP, log(GRP^{pc})						
	Benchmark		**Country-Year FE**		**Spatial Correlation**	
	FE-OLS (1)	2SLS (2)	FE-OLS (3)	2SLS (4)	FE-OLS (5)	2SLS (6)
	Panel A: Regression results (second stage)					
Ethnic inequality	-0.0354***	-0.0450***	-0.0062***	-0.00826**	-0.0063***	-0.0082***
	(0.0103)	(0.0137)	(0.0018)	(0.0033)	(0.0018)	(0.0033)
log(GRP^{pc})($t-1$)	0.741***	0.738***	0.710***	0.709***	0.710***	0.709***
	(0.183)	(0.183)	(0.0444)	(0.0446)	(0.0444)	(0.0447)
log(GRP^{pc})($t-2$)	0.216	0.216	0.172***	0.172***	0.173***	0.172***
	(0.190)	(0.189)	(0.0299)	(0.0298)	(0.0299)	(0.0298)
log(GRP^{pc})($t-3$)	-0.00446	-0.00410	0.0611**	0.0610**	0.0611**	0.0610**
	(0.0345)	(0.0344)	(0.0277)	(0.0277)	(0.0277)	(0.0277)
log(GRP^{pc})($t-4$)	-0.0341	-0.0350	0.0452*	0.0451*	0.0449*	0.0449*
	(0.0278)	(0.0279)	(0.0226)	(0.0226)	(0.0226)	(0.0226)
	Panel B: First-stage regression results					
Spatial Instrument	–	0.953***	–	0.916***	–	0.917***
		(0.0639)		(0.0627)		(0.0626)
Observations	9,280	9,280	9,280	9,280	9,280	9,280
Sub-national Units	589	589	589	589	589	589
R-Squared	0.908	0.908	0.985	0.985	0.985	0.985
F Stat (second)	2846	1809	58325	54124	48634	44639
K-P F-Stat (first)	–	222.5	–	213.3	–	214.9
S-Y 10% max IV size	–	16.38	–	16.38	–	16.38
S-W p-val	–	0.000	–	0.000	–	0.000
Country Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Period Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Country-Year Fixed Effects	No	No	Yes	Yes	Yes	Yes
Spatial Correlation	No	No	No	No	Yes	Yes

Notes: Cluster robust standard errors (on the country level) are reported in parentheses. The dependent variable is the log of real per capita GRP, measured using data from Leßmann and Seidel (2017). Ethnic inequality is measured as described in Section (2) using differences in nighttime lights across ethnic homelands. The table presents estimates from three models, each estimated with the traditional within group estimator (columns labeled "FE-OLS") and with 2SLS using an adjusted version of our spatial instrumental variable that only considers ethnic groups outside the home country of the sub-national regions for which the instrument is constructed. The first model ("Benchmark") replicates the specification of the country-level dynamic panel data model of Section (3.2), the second specification ("Country-Year FE") accounts for time-varying unobservables on the country level by including country-year fixed effects. The third specification ("Spatial Correlation") accounts for spatial correlation between the GRP of sub-national units and a the average of GRP in other sub-national units of the same country, weighted by the inverse of the distance between sub-national units. The row labeled "K-P F-Stat (first)" reports the F-statistic of the Kleibergen-Paap rk Wald test, which is a robust test for weak identification in case the errors are not i.i.d. We also report Stock-Yogo thresholds for the Kleibergen-Paap weak identification test for a demanding critical value of 10% max IV size (labeled "S-Y 10% max IV size"). The row labeled "S-W p-val" presents p-values of the Stock-Wright LM test, presenting weak-instrument-robust inference. The null of this test is that the endogenous regressor is equal to zero. The test is robust to the presence of weak instruments.

*** Significant at the 1 percent level,
** Significant at the 5 percent level,
* Significant at the 10 percent level

Table C-16 ETHNIC INEQUALITY AND ECONOMIC GROWTH—SUB-NATIONAL ESTIMATES, AFRICAN REGIONS, TWO-WAY CLUSTERING (COUNTRY AND ADM1-LEVEL), 1992–2012

Dependent variable: Real per capita GRP, $\log(\text{GRP}^{pc})$						
	Benchmark		**Country-Year FE**		**Spatial Correlation**	
	FE-OLS (1)	2SLS (2)	FE-OLS (3)	2SLS (4)	FE-OLS (5)	2SLS (6)
	Panel A: Regression results (second stage)					
Ethnic inequality	-0.0354***	-0.0450***	-0.0062***	-0.0083**	-0.0063***	-0.0082**
	(0.0103)	(0.0137)	(0.0018)	(0.0033)	(0.0018)	(0.0033)
$\log(\text{GRP}^{pc})(t-1)$	0.741***	0.738***	0.710***	0.709***	0.710***	0.709***
	(0.183)	(0.183)	(0.0444)	(0.0446)	(0.0444)	(0.0447)
$\log(\text{GRP}^{pc})(t-2)$	0.216	0.216	0.172***	0.172***	0.173***	0.172***
	(0.190)	(0.189)	(0.0299)	(0.0298)	(0.0299)	(0.0298)
$\log(\text{GRP}^{pc})(t-3)$	-0.00446	-0.00410	0.0611**	0.0610**	0.0611**	0.0610**
	(0.0345)	(0.0344)	(0.0277)	(0.0277)	(0.0277)	(0.0277)
$\log(\text{GRP}^{pc})(t-4)$	-0.0341	-0.0350	0.0452*	0.0451*	0.0449*	0.0449*
	(0.0278)	(0.0279)	(0.0226)	(0.0226)	(0.0226)	(0.0226)
	Panel B: First-stage regression results					
Spatial Instrument	–	0.953***	–	0.916***	–	0.917***
		(0.0639)		(0.0627)		(0.0626)
Observations	9,280	9,280	9,280	9,280	9,280	9,280
Sub-national Units	589	589	589	589	589	589
R-Squared	0.908	0.908	0.985	0.985	0.985	0.985
F Stat (second)	2846	1809	58325	54124	48634	44639
K-P F-Stat (first)	–	222.5	–	213.3	–	214.9
S-Y 10% max IV size	–	16.38	–	16.38	–	16.38
S-W p-val	–	0.000	–	0.000	–	0.000
Country Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Period Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Country-Year Fixed Effects	No	No	Yes	Yes	Yes	Yes
Spatial Correlation	No	No	No	No	Yes	Yes

Notes: Cluster robust standard errors (on the country level) are reported in parentheses. The dependent variable is the log of real per capita GRP, measured using data from Leßmann and Seidel (2017). Ethnic inequality is measured as described in Section (2) using differences in nighttime lights across ethnic homelands. The table presents estimates from three models, each estimated with the traditional within group estimator (columns labeled "FE-OLS") and with 2SLS using an adjusted version of our spatial instrumental variable that only considers ethnic groups outside the home country of the sub-national regions for which the instrument is constructed. The first model ("Benchmark") replicates the specification of the country-level dynamic panel data model of Section (3.2), the second specification ("Country-Year FE") accounts for time-varying unobservables on the country level by including country-year fixed effects. The third specification ("Spatial Correlation") accounts for spatial correlation between the GRP of sub-national units and a the average of GRP in other sub-national units of the same country, weighted by the inverse of the distance between sub-national units. The row labeled "K-P F-Stat (first)" reports the F-statistic of the Kleibergen-Paap rk Wald test, which is a robust test for weak identification in case the errors are not i.i.d. We also report Stock-Yogo thresholds for the Kleibergen-Paap weak identification test for a demanding critical value of 10% max IV size (labeled "S-Y 10% max IV size"). The row labeled "S-W p-val" presents p-values of the Stock-Wright LM test, presenting weak-instrument-robust inference. The null of this test is that the endogenous regressor is equal to zero. The test is robust to the presence of weak instruments.

*** Significant at the 1 percent level,
** Significant at the 5 percent level,
* Significant at the 10 percent level

Table C-17 ETHNIC INEQUALITY AND ECONOMIC GROWTH—SUB-NATIONAL ESTIMATES, AFRICAN REGIONS, ACCOUNTING FOR POPULATION INEQUALITY, 1992–2012

Dependent variable: Real per capita GRP, $\log(\text{GRP}^{pc})$

	Benchmark		**Country-Year FE**		**Spatial Correlation**	
	FE-OLS (1)	2SLS (2)	FE-OLS (3)	2SLS (4)	FE-OLS (5)	2SLS (6)
	Panel A: Regression results (second stage)					
Ethnic inequality	-0.0321***	-0.0503***	-0.0069***	-0.0116***	-0.0070***	-0.0114***
	(0.0048)	(0.0113)	(0.0018)	(0.0036)	(0.0018)	(0.0036)
Population Inequality	-0.0054	0.0066	0.0012	0.0041	0.0013	0.0040
	(0.0041)	(0.0074)	(0.0016)	(0.0025)	(0.0016)	(0.0025)
$\log(\text{GRP}^{pc})(t-1)$	0.741***	0.738***	0.710***	0.709***	0.710***	0.709***
	(0.0449)	(0.0448)	(0.0265)	(0.0264)	(0.0265)	(0.0264)
$\log(\text{GRP}^{pc})(t-2)$	0.216***	0.216***	0.172***	0.172***	0.172***	0.172***
	(0.0510)	(0.0508)	(0.0225)	(0.0225)	(0.0225)	(0.0224)
$\log(\text{GRP}^{pc})(t-3)$	-0.00438	-0.00414	0.0612**	0.0612**	0.0611**	0.0611**
	(0.0177)	(0.0177)	(0.0286)	(0.0286)	(0.0286)	(0.0286)
$\log(\text{GRP}^{pc})(t-4)$	-0.0342***	-0.0349***	0.0452**	0.0453**	0.0450**	0.0451**
	(0.0127)	(0.0126)	(0.0207)	(0.0207)	(0.0207)	(0.0207)
	Panel B: First-stage regression results					
Spatial Instrument	–	0.638***	–	0.622***	–	0.623***
		(0.0591)		(0.0625)		(0.0623)
Observations	9,280	9,280	9,280	9,280	9,280	9,280
Sub-national Units	589	589	589	589	589	589
R-Squared	0.908	0.907	0.985	0.985	0.985	0.985
F Stat (second)	3717.7	3613.6	91877	91698	80935	807156
K-P F-Stat (first)	–	116.32	–	99.02	–	100.16
S-Y 10% max IV size	–	16.38	–	16.38	–	16.38
S-W p-val	–	0.000	–	0.000	–	0.000
Country Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Period Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Country-Year Fixed Effects	No	No	Yes	Yes	Yes	Yes
Spatial Correlation	No	No	No	No	Yes	Yes

Notes: Cluster robust standard errors (on the ADM1 level) are reported in parentheses. The dependent variable is the log of real per capita GRP, measured using data from Leßmann and Seidel (2017). Ethnic inequality is measured as described in Section (2) using differences in nighttime lights across ethnic homelands. The table presents estimates from three models, each estimated with the traditional within group estimator (columns labeled "FE-OLS") and with 2SLS using an adjusted version of our spatial instrumental variable that only considers ethnic groups outside the home country of the sub-national regions for which the instrument is constructed. The first model ("Benchmark") replicates the specification of the country-level dynamic panel data model of Section (3.2), the second specification ("Country-Year FE") accounts for time-varying unobservables on the country level by including country-year fixed effects. The third specification ("Spatial Correlation") accounts for spatial correlation between the GRP of sub-national units and a the average of GRP in other sub-national units of the same country, weighted by the inverse of the distance between sub-national units. The row labeled "K-P F-Stat (first)" reports the F-statistic of the Kleibergen-Paap rk Wald test, which is a robust test for weak identification in case the errors are not i.i.d. We also report Stock-Yogo thresholds for the Kleibergen-Paap weak identification test for a demanding critical value of 10% max IV size (labeled "S-Y 10% max IV size"). The row labeled "S-W p-val" presents p-values of the Stock-Wright LM test, presenting weak-instrument-robust inference. The null of this test is that the endogenous regressor is equal to zero. The test is robust to the presence of weak instruments.

*** Significant at the 1 percent level,
** Significant at the 5 percent level,
* Significant at the 10 percent level

Table C-18 ETHNIC INEQUALITY AND ECONOMIC GROWTH—SUB-NATIONAL ESTIMATES, ALL REGIONS, 1992–2012

Dependent variable: Real per capita GRP, $\log(\text{GRP}^{pc})$						
	Benchmark		**Country-Year FE**		**Spatial Correlation**	
	FE-OLS (1)	2SLS (2)	FE-OLS (3)	2SLS (4)	FE-OLS (5)	2SLS (6)
	Panel A: Regression results (second stage)					
Ethnic inequality	-0.0251***	-0.0302***	-0.0083***	-0.0087***	-0.0083***	-0.0086***
	(0.0017)	(0.0025)	(0.0009)	(0.0012)	(0.0009)	(0.0012)
$\log(\text{GRP}^{pc})(t-1)$	0.844***	0.843***	0.571***	0.571***	0.571***	0.571***
	(0.0193)	(0.0193)	(0.0139)	(0.0139)	(0.0139)	(0.0139)
$\log(\text{GRP}^{pc})(t-2)$	0.187***	0.186***	0.254***	0.254***	0.254***	0.254***
	(0.0196)	(0.0196)	(0.0117)	(0.0117)	(0.0116)	(0.0117)
$\log(\text{GRP}^{pc})(t-3)$	-0.0451***	-0.0450***	0.0986***	0.0986***	0.0986***	0.0986***
	(0.00930)	(0.00929)	(0.0140)	(0.0140)	(0.0140)	(0.0140)
$\log(\text{GRP}^{pc})(t-4)$	-0.0427***	-0.0434***	0.0595***	0.0595***	0.0595***	0.0595***
	(0.00727)	(0.00728)	(0.00970)	(0.00970)	(0.00970)	(0.00970)
	Panel B: First-stage regression results					
Spatial Instrument	–	0.853***	–	0.819***	–	0.820***
		(0.0224)		(0.0241)		(0.0241)
Observations	41,411	41,411	41,411	41,411	41,411	41,411
Sub-national Units	2,637	2,637	2,637	2,637	2,637	2,637
R-Squared	0.921	0.920	0.981	0.981	0.981	0.981
F Stat (second)	31613	29768	237028	240410	199223	202217
K-P F-Stat (first)	–	1448	–	1155	–	1158
S-Y 10% max IV size	–	16.38	–	16.38	–	16.38
S-W p-val	–	0.000	–	0.000	–	0.000
Country Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Period Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Country-Year Fixed Effects	No	No	Yes	Yes	Yes	Yes
Spatial Correlation	No	No	No	No	Yes	Yes

Notes: Cluster robust standard errors (on the ADM1 level) are reported in parentheses. The dependent variable is the log of real per capita GRP, measured using data from Leßmann and Seidel (2017). Ethnic inequality is measured as described in Section (2) using differences in nighttime lights across ethnic homelands. The table presents estimates from three models, each estimated with the traditional within group estimator (columns labeled "FE-OLS") and with 2SLS using our spatial instrumental variable. The first model ("Benchmark") replicates the specification of the country-level dynamic panel data model of Section (3.2), the second specification ("Country-Year FE") accounts for time-varying unobservables on the country level by including country-year fixed effects. The third specification ("Spatial Correlation") accounts for spatial correlation between the GRP of sub-national units and a the average of GRP in other sub-national units of the same country, weighted by the inverse of the distance between sub-national units. The row labeled "K-P F-Stat (first)" reports the F-statistic of the Kleibergen-Paap rk Wald test, which is a robust test for weak identification in case the errors are not i.i.d. We also report Stock-Yogo thresholds for the Kleibergen-Paap weak identification test for a demanding critical value of 10% max IV size (labeled "S-Y 10% max IV size"). The row labeled "S-W p-val" presents p-values of the Stock-Wright LM test, presenting weak-instrument-robust inference. The null of this test is that the endogenous regressor is equal to zero. The test is robust to the presence of weak instruments.

*** Significant at the 1 percent level,
** Significant at the 5 percent level,
* Significant at the 10 percent level

Table C-19 ETHNIC INEQUALITY AND ECONOMIC GROWTH—SUB-NATIONAL ESTIMATES, ALL REGIONS, WEIGHTED MEASURE OF SUB-NATIONAL ETHNIC INEQUALITY, 1992–2012

Dependent variable: Real per capita GRP, log(GRP^{pc})

	Benchmark		**Country-Year FE**		**Spatial Correlation**	
	FE-OLS (1)	2SLS (2)	FE-OLS (3)	2SLS (4)	FE-OLS (5)	2SLS (6)
	Panel A: Regression results (second stage)					
Ethnic inequality	-0.0339***	-0.0487***	-0.0112***	-0.0142***	-0.0112***	-0.0141***
	(0.0028)	(0.0055)	(0.0016)	(0.0029)	(0.0016)	(0.0029)
log(GRP^{pc})$(t-1)$	0.847***	0.845***	0.572***	0.572***	0.572***	0.571***
	(0.0193)	(0.0192)	(0.0139)	(0.0139)	(0.0139)	(0.0138)
log(GRP^{pc})$(t-2)$	0.186***	0.186***	0.255***	0.254***	0.255***	0.254***
	(0.0197)	(0.0196)	(0.0117)	(0.0117)	(0.0117)	(0.0117)
log(GRP^{pc})$(t-3)$	-0.0454***	-0.0453***	0.0984***	0.0984***	0.0984***	0.0984***
	(0.00931)	(0.00929)	(0.0140)	(0.0140)	(0.0140)	(0.0140)
log(GRP^{pc})$(t-4)$	-0.0411***	-0.0419***	0.0597***	0.0597***	0.0596***	0.0597***
	(0.00726)	(0.00725)	(0.00972)	(0.00972)	(0.00972)	(0.00972)
	Panel B: First-stage regression results					
Spatial Instrument	–	0.483***	–	0.467***	–	0.467***
		(0.0288)		(0.0299)		(0.0300)
Observations	41,412	41,412	41,412	41,412	41,412	41,412
Sub-national Units	2,637	2,637	2,637	2,637	2,637	2,637
R-Squared	0.920	0.920	0.981	0.981	0.981	0.981
F Stat (second)	23430	22691	230298	227321	193463	191053
K-P F-Stat (first)	–	282	–	243	–	243
S-Y 10% max IV size	–	16.38	–	16.38	–	16.38
S-W p-val	–	0.000	–	0.000	–	0.000
Country Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Period Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Country-Year Fixed Effects	No	No	Yes	Yes	Yes	Yes
Spatial Correlation	No	No	No	No	Yes	Yes

Notes: Cluster robust standard errors (on the ADM1 level) are reported in parentheses. The dependent variable is the log of real per capita GRP, measured using data from Leßmann and Seidel (2017). Ethnic inequality is measured as described in Section (2) using differences in nighttime lights across ethnic homelands. The table presents estimates from three models, each estimated with the traditional within group estimator (columns labeled "FE-OLS") and with 2SLS using our spatial instrumental variable. The first model ("Benchmark") replicates the specification of the country-level dynamic panel data model of Section (3.2), the second specification ("Country-Year FE") accounts for time-varying unobservables on the country level by including country-year fixed effects. The third specification ("Spatial Correlation") accounts for spatial correlation between the GRP of sub-national units and a the average of GRP in other sub-national units of the same country, weighted by the inverse of the distance between sub-national units. The row labeled "K-P F-Stat (first)" reports the F-statistic of the Kleibergen-Paap rk Wald test, which is a robust test for weak identification in case the errors are not i.i.d. We also report Stock-Yogo thresholds for the Kleibergen-Paap weak identification test for a demanding critical value of 10% max IV size (labeled "S-Y 10% max IV size"). The row labeled "S-W p-val" presents p-values of the Stock-Wright LM test, presenting weak-instrument-robust inference. The null of this test is that the endogenous regressor is equal to zero. The test is robust to the presence of weak instruments.

*** Significant at the 1 percent level,
** Significant at the 5 percent level,
* Significant at the 10 percent level

Table C-20 ETHNIC INEQUALITY AND ECONOMIC GROWTH—SUB-NATIONAL ESTIMATES, ALL REGIONS, EXCLUDING SUB-NATIONAL REGIONS WITH BORDER-CHANGES, 1992–2012

Dependent variable: Real per capita GRP, log(GRP^{pc})						
	Benchmark		**Country-Year FE**		**Spatial Correlation**	
	FE-OLS (1)	2SLS (2)	FE-OLS (3)	2SLS (4)	FE-OLS (5)	2SLS (6)
	Panel A: Regression results (second stage)					
Ethnic inequality	-0.0260***	-0.0323***	-0.0079***	-0.0082***	-0.0074***	-0.0082***
	(0.0018)	(0.0027)	(0.0009)	(0.0013)	(0.0009)	(0.0013)
log(GRP^{pc})($t-1$)	0.830***	0.829***	0.569***	0.569***	0.569***	0.569***
	(0.0205)	(0.0205)	(0.0149)	(0.0149)	(0.0149)	(0.0149)
log(GRP^{pc})($t-2$)	0.206***	0.206***	0.267***	0.267***	0.267***	0.267***
	(0.0207)	(0.0207)	(0.0124)	(0.0124)	(0.0124)	(0.0124)
log(GRP^{pc})($t-3$)	-0.0447***	-0.0446***	0.0853***	0.0853***	0.0853***	0.0853***
	(0.00979)	(0.00978)	(0.0152)	(0.0152)	(0.0152)	(0.0152)
log(GRP^{pc})($t-4$)	-0.0504***	-0.0513***	0.0615***	0.0615***	0.0614***	0.0614***
	(0.00767)	(0.00768)	(0.0110)	(0.0110)	(0.0110)	(0.0110)
	Panel B: First-stage regression results					
Spatial Instrument	–	0.857***	–	0.818***	–	0.818***
		(0.0229)		(0.0246)		(0.0246)
Observations	37171	37171	37171	37171	37171	37171
Sub-national Units	2,525	2,525	2,525	2,525	2,525	2,525
R-Squared	0.917	0.917	0.981	0.981	0.981	0.981
F Stat (second)	29369	28977	189393	192856	159241	162267
K-P F-Stat (first)	–	1404	–	1104	–	1105
S-Y 10% max IV size	–	16.38	–	16.38	–	16.38
S-W p-val	–	0.000	–	0.000	–	0.000
Country Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Period Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Country-Year Fixed Effects	No	No	Yes	Yes	Yes	Yes
Spatial Correlation	No	No	No	No	Yes	Yes

Notes: Cluster robust standard errors (on the ADM1 level) are reported in parentheses. The dependent variable is the log of real per capita GRP, measured using data from Leßmann and Seidel (2017). The table reports estimates when we exclude sub-national regions with border changes. Ethnic inequality is measured as described in Section (2) using differences in nighttime lights across ethnic homelands. The table presents estimates from three models, each estimated with the traditional within group estimator (columns labeled "FE-OLS") and with 2SLS using our spatial instrumental variable. The first model ("Benchmark") replicates the specification of the country-level dynamic panel data model of Section (3.2), the second specification ("Country-Year FE") accounts for time-varying unobservables on the country level by including country-year fixed effects. The third specification ("Spatial Correlation") accounts for spatial correlation between the GRP of sub-national units and a the average of GRP in other sub-national units of the same country, weighted by the inverse of the distance between sub-national units. The row labeled "K-P F-Stat (first)" reports the F-statistic of the Kleibergen-Paap rk Wald test, which is a robust test for weak identification in case the errors are not i.i.d. We also report Stock-Yogo thresholds for the Kleibergen-Paap weak identification test for a demanding critical value of 10% max IV size (labeled "S-Y 10% max IV size"). The row labeled "S-W p-val" presents p-values of the Stock-Wright LM test, presenting weak-instrument-robust inference. The null of this test is that the endogenous regressor is equal to zero. The test is robust to the presence of weak instruments.

*** Significant at the 1 percent level,
** Significant at the 5 percent level,
* Significant at the 10 percent level

Table C-21 ETHNIC INEQUALITY AND ECONOMIC GROWTH—SUB-NATIONAL ESTIMATES, ALL REGIONS, ALTERNATIVE SPECIFICATION OF THE INSTRUMENTAL VARIABLE, 1992–2012

Dependent variable: Real per capita GRP, log(GRP^{pc})						
	Benchmark		**Country-Year FE**		**Spatial Correlation**	
	FE-OLS (1)	2SLS (2)	FE-OLS (3)	2SLS (4)	FE-OLS (5)	2SLS (6)
	Panel A: Regression results (second stage)					
Ethnic inequality	-0.0251***	-0.0323***	-0.00832***	-0.00932***	-0.00833***	-0.00920***
	(0.0017)	(0.0025)	(0.0009)	(0.0012)	(0.0009)	(0.0012)
log(GRP^{pc})$(t-1)$	0.844***	0.843***	0.571***	0.570***	0.571***	0.570***
	(0.0193)	(0.0193)	(0.0139)	(0.0139)	(0.0139)	(0.0139)
log(GRP^{pc})$(t-2)$	0.187***	0.187***	0.254***	0.254***	0.254***	0.254***
	(0.0196)	(0.0196)	(0.0117)	(0.0116)	(0.0116)	(0.0116)
log(GRP^{pc})$(t-3)$	-0.0450***	-0.0449***	0.0986***	0.0986***	0.0986***	0.0986***
	(0.00930)	(0.00929)	(0.0140)	(0.0140)	(0.0140)	(0.0140)
log(GRP^{pc})$(t-4)$	-0.0428***	-0.0438***	0.0596***	0.0596***	0.0595***	0.0595***
	(0.0073)	(0.0073)	(0.0097)	(0.0097)	(0.0097)	(0.0097)
	Panel B: First-stage regression results					
Spatial Instrument	–	0.748***	–	0.737***	–	0.739***
		(0.0179)		(0.0198)		(0.0198)
Observations	41,406	41,406	41,406	41,406	41,406	41,406
Sub-national Units	2,637	2,637	2,637	2,637	2,637	2,637
R-Squared	0.921	0.920	0.981	0.981	0.981	0.981
F Stat (second)	31609	30458	236947	247036	199151	208110
K-P F-Stat (first)	–	1741	–	1387	–	1397
S-Y 10% max IV size	–	16.38	–	16.38	–	16.38
S-W p-val	–	0.000	–	0.000	–	0.000
Country Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Period Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Country-Year Fixed Effects	No	No	Yes	Yes	Yes	Yes
Spatial Correlation	No	No	No	No	Yes	Yes

Notes: Cluster robust standard errors (on the ADM1 level) are reported in parentheses. The dependent variable is the log of real per capita GRP, measured using data from Leßmann and Seidel (2017). Ethnic inequality is measured as described in Section (2) using differences in nighttime lights across ethnic homelands. The table presents estimates from three models, each estimated with the traditional within group estimator (columns labeled "FE-OLS") and with 2SLS using an adjusted version of our spatial instrumental variable that only considers ethnic groups outside the home country of the sub-national regions for which the instrument is constructed. The first model ("Benchmark") replicates the specification of the country-level dynamic panel data model of Section (3.2), the second specification ("Country-Year FE") accounts for time-varying unobservables on the country level by including country-year fixed effects. The third specification ("Spatial Correlation") accounts for spatial correlation between the GRP of sub-national units and a the average of GRP in other sub-national units of the same country, weighted by the inverse of the distance between sub-national units. The row labeled "K-P F-Stat (first)" reports the F-statistic of the Kleibergen-Paap rk Wald test, which is a robust test for weak identification in case the errors are not i.i.d. We also report Stock-Yogo thresholds for the Kleibergen-Paap weak identification test for a demanding critical value of 10% max IV size (labeled "S-Y 10% max IV size"). The row labeled "S-W p-val" presents p-values of the Stock-Wright LM test, presenting weak-instrument-robust inference. The null of this test is that the endogenous regressor is equal to zero. The test is robust to the presence of weak instruments.

*** Significant at the 1 percent level,
** Significant at the 5 percent level,
* Significant at the 10 percent level

Table C-22 ETHNIC INEQUALITY AND ECONOMIC GROWTH—SUB-NATIONAL ESTIMATES, ALL REGIONS, ALTERNATIVE CLUSTERING (COUNTRY-LEVEL), 1992–2012

Dependent variable: Real per capita GRP, $\log(GRP^{pc})$						
	Benchmark		**Country-Year FE**		**Spatial Correlation**	
	FE-OLS (1)	2SLS (2)	FE-OLS (3)	2SLS (4)	FE-OLS (5)	2SLS (6)
	Panel A: Regression results (second stage)					
Ethnic inequality	-0.0251***	-0.0302***	-0.0083***	-0.0087***	-0.0083***	-0.0086***
	(0.0038)	(0.0050)	(0.0011)	(0.0015)	(0.0011)	(0.0015)
$\log(GRP^{pc})(t-1)$	0.844***	0.843***	0.571***	0.571***	0.571***	0.571***
	(0.0797)	(0.0797)	(0.0265)	(0.0264)	(0.0265)	(0.0264)
$\log(GRP^{pc})(t-2)$	0.187**	0.186**	0.254***	0.254***	0.254***	0.254***
	(0.0778)	(0.0776)	(0.0148)	(0.0148)	(0.0148)	(0.0148)
$\log(GRP^{pc})(t-3)$	-0.0451	-0.0450	0.0986***	0.0986***	0.0986***	0.0986***
	(0.0472)	(0.0472)	(0.0245)	(0.0245)	(0.0245)	(0.0245)
$\log(GRP^{pc})(t-4)$	-0.0427	-0.0434	0.0595***	0.0595***	0.0595***	0.0595***
	(0.0417)	(0.0417)	(0.0130)	(0.0130)	(0.0130)	(0.0130)
	Panel B: First-stage regression results					
Spatial Instrument	–	0.853***	–	0.819***	–	0.820***
		(0.0320)		(0.0328)		(0.0328)
Observations	41,411	41,411	41,411	41,411	41,411	41,411
Sub-national Units	2,637	2,637	2,637	2,637	2,637	2,637
R-Squared	0.921	0.920	0.981	0.981	0.981	0.981
F Stat (second)	12215	8517	141198	144103	118296	120098
K-P F-Stat (first)	–	714	–	624	–	626
S-Y 10% max IV size	–	16.38	–	16.38	–	16.38
S-W p-val	–	0.000	–	0.000	–	0.000
Country Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Period Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Country-Year Fixed Effects	No	No	Yes	Yes	Yes	Yes
Spatial Correlation	No	No	No	No	Yes	Yes

Notes: Cluster robust standard errors (on the country level) are reported in parentheses. The dependent variable is the log of real per capita GRP, measured using data from Leßmann and Seidel (2017). Ethnic inequality is measured as described in Section (2) using differences in nighttime lights across ethnic homelands. The table presents estimates from three models, each estimated with the traditional within group estimator (columns labeled "FE-OLS") and with 2SLS using an adjusted version of our spatial instrumental variable that only considers ethnic groups outside the home country of the sub-national regions for which the instrument is constructed. The first model ("Benchmark") replicates the specification of the country-level dynamic panel data model of Section (3.2), the second specification ("Country-Year FE") accounts for time-varying unobservables on the country level by including country-year fixed effects. The third specification ("Spatial Correlation") accounts for spatial correlation between the GRP of sub-national units and a the average of GRP in other sub-national units of the same country, weighted by the inverse of the distance between sub-national units. The row labeled "K-P F-Stat (first)" reports the F-statistic of the Kleibergen-Paap rk Wald test, which is a robust test for weak identification in case the errors are not i.i.d. We also report Stock-Yogo thresholds for the Kleibergen-Paap weak identification test for a demanding critical value of 10% max IV size (labeled "S-Y 10% max IV size"). The row labeled "S-W p-val" presents p-values of the Stock-Wright LM test, presenting weak-instrument-robust inference. The null of this test is that the endogenous regressor is equal to zero. The test is robust to the presence of weak instruments.

*** Significant at the 1 percent level,
** Significant at the 5 percent level,
* Significant at the 10 percent level

Table C-23 ETHNIC INEQUALITY AND ECONOMIC GROWTH—SUB-NATIONAL ESTIMATES, ALL REGIONS, TWO-WAY CLUSTERING (COUNTRY AND ADM1-LEVEL), 1992–2012

Dependent variable: Real per capita GRP, log(GRP^{pc})						
	Benchmark		**Country-Year FE**		**Spatial Correlation**	
	FE-OLS (1)	2SLS (2)	FE-OLS (3)	2SLS (4)	FE-OLS (5)	2SLS (6)
	Panel A: Regression results (second stage)					
Ethnic inequality	-0.0251***	-0.0302***	-0.0083***	-0.0087***	-0.0083***	-0.0086***
	(0.0038)	(0.0050)	(0.0011)	(0.0015)	(0.0011)	(0.0015)
log(GRP^{pc})($t-1$)	0.844***	0.843***	0.571***	0.571***	0.571***	0.571***
	(0.0797)	(0.0797)	(0.0265)	(0.0264)	(0.0265)	(0.0264)
log(GRP^{pc})($t-2$)	0.187**	0.186**	0.254***	0.254***	0.254***	0.254***
	(0.0778)	(0.0776)	(0.0148)	(0.0148)	(0.0148)	(0.0148)
log(GRP^{pc})($t-3$)	-0.0451	-0.0450	0.0986***	0.0986***	0.0986***	0.0986***
	(0.0472)	(0.0472)	(0.0245)	(0.0245)	(0.0245)	(0.0245)
log(GRP^{pc})($t-4$)	-0.0251***	-0.0302***	-0.00832***	-0.00865***	-0.00834***	-0.00856***
	(0.00381)	(0.00503)	(0.00106)	(0.00147)	(0.00105)	(0.00147)
	Panel B: First-stage regression results					
Spatial Instrument	–	0.853***	–	0.819***	–	0.820***
		(0.0319)		(0.0328)		(0.0328)
Observations	41,411	41,411	41,411	41,411	41,411	41,411
Sub-national Units	2,637	2,637	2,637	2,637	2,637	2,637
R-Squared	0.921	0.920	0.981	0.981	0.981	0.981
F Stat (second)	12215	8517	141198	144103	118296	120098
K-P F-Stat (first)	–	714	–	624	–	626
S-Y 10% max IV size	–	16.38	–	16.38	–	16.38
S-W p-val	–	0.000	–	0.000	–	0.000
Country Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Period Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Country-Year Fixed Effects	No	No	Yes	Yes	Yes	Yes
Spatial Correlation	No	No	No	No	Yes	Yes

Notes: Cluster robust standard errors (on the country level) are reported in parentheses. The dependent variable is the log of real per capita GRP, measured using data from Leßmann and Seidel (2017). Ethnic inequality is measured as described in Section (2) using differences in nighttime lights across ethnic homelands. The table presents estimates from three models, each estimated with the traditional within group estimator (columns labeled "FE-OLS") and with 2SLS using an adjusted version of our spatial instrumental variable that only considers ethnic groups outside the home country of the sub-national regions for which the instrument is constructed. The first model ("Benchmark") replicates the specification of the country-level dynamic panel data model of Section (3.2), the second specification ("Country-Year FE") accounts for time-varying unobservables on the country level by including country-year fixed effects. The third specification ("Spatial Correlation") accounts for spatial correlation between the GRP of sub-national units and a the average of GRP in other sub-national units of the same country, weighted by the inverse of the distance between sub-national units. The row labeled "K-P F-Stat (first)" reports the F-statistic of the Kleibergen-Paap rk Wald test, which is a robust test for weak identification in case the errors are not i.i.d. We also report Stock-Yogo thresholds for the Kleibergen-Paap weak identification test for a demanding critical value of 10% max IV size (labeled "S-Y 10% max IV size"). The row labeled "S-W p-val" presents p-values of the Stock-Wright LM test, presenting weak-instrument-robust inference. The null of this test is that the endogenous regressor is equal to zero. The test is robust to the presence of weak instruments.

*** Significant at the 1 percent level,
** Significant at the 5 percent level,
* Significant at the 10 percent level

Table C-24 ETHNIC INEQUALITY AND ECONOMIC GROWTH—SUB-NATIONAL ESTIMATES, ALL REGIONS, ACCOUNTING FOR POPULATION INEQUALITY, 1992–2012

Dependent variable: Real per capita GRP, $\log(\text{GRP}^{pc})$

	Benchmark		**Country-Year FE**		**Spatial Correlation**	
	FE-OLS (1)	2SLS (2)	FE-OLS (3)	2SLS (4)	FE-OLS (5)	2SLS (6)
	Panel A: Regression results (second stage)					
Ethnic inequality	-0.0271***	-0.0392***	-0.0096***	-0.0115***	-0.0096***	-0.0113***
	(0.0019)	(0.0039)	(0.0010)	(0.0019)	(0.0010)	(0.0019)
Population Inequality	0.0028***	0.0086***	0.0018***	0.0026***	0.0018***	0.0026**
	(0.0010)	(0.0019)	(0.0006)	(0.0010)	(0.0006)	(0.0010)
$\log(\text{GRP}^{pc})(t-1)$	0.844***	0.843***	0.571***	0.570***	0.571***	0.570***
	(0.0193)	(0.0192)	(0.0139)	(0.0139)	(0.0139)	(0.0139)
$\log(\text{GRP}^{pc})(t-2)$	0.187***	0.186***	0.254***	0.254***	0.254***	0.254***
	(0.0196)	(0.0196)	(0.0116)	(0.0116)	(0.0116)	(0.0116)
$\log(\text{GRP}^{pc})(t-3)$	-0.0451***	-0.0450***	0.0986***	0.0986***	0.0986***	0.0986***
	(0.0093)	(0.0093)	(0.0140)	(0.0140)	(0.0140)	(0.0140)
$\log(\text{GRP}^{pc})(t-4)$	-0.0427***	-0.0437***	0.0596***	0.0596***	0.0596***	0.0596***
	(0.0073)	(0.0072)	(0.0097)	(0.0097)	(0.0097)	(0.0097)
	Panel B: First-stage regression results					
Spatial Instrument	–	0.594***	–	0.571***	–	0.572***
		(0.0265)		(0.0280)		(0.0279)
Observations	41,411	41,411	41,411	41,411	41,411	41,411
Sub-national Units	2,637	2,637	2,637	2,637	2,637	2,637
R-Squared	0.921	0.920	0.981	0.981	0.981	0.981
F Stat (second)	12215	8517	141198	144103	118296	120098
K-P F-Stat (first)	–	500	–	419	–	421
S-Y 10% max IV size	–	16.38	–	16.38	–	16.38
S-W p-val	–	0.000	–	0.000	–	0.000
Country Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Period Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Country-Year Fixed Effects	No	No	Yes	Yes	Yes	Yes
Spatial Correlation	No	No	No	No	Yes	Yes

Notes: Cluster robust standard errors (on the ADM1 level) are reported in parentheses. The dependent variable is the log of real per capita GRP, measured using data from Leßmann and Seidel (2017). Ethnic inequality is measured as described in Section (2) using differences in nighttime lights across ethnic homelands. The table presents estimates from three models, each estimated with the traditional within group estimator (columns labeled "FE-OLS") and with 2SLS using an adjusted version of our spatial instrumental variable that only considers ethnic groups outside the home country of the sub-national regions for which the instrument is constructed. The first model ("Benchmark") replicates the specification of the country-level dynamic panel data model of Section (3.2), the second specification ("Country-Year FE") accounts for time-varying unobservables on the country level by including country-year fixed effects. The third specification ("Spatial Correlation") accounts for spatial correlation between the GRP of sub-national units and a the average of GRP in other sub-national units of the same country, weighted by the inverse of the distance between sub-national units. The row labeled "K-P F-Stat (first)" reports the F-statistic of the Kleibergen-Paap rk Wald test, which is a robust test for weak identification in case the errors are not i.i.d. We also report Stock-Yogo thresholds for the Kleibergen-Paap weak identification test for a demanding critical value of 10% max IV size (labeled "S-Y 10% max IV size"). The row labeled "S-W p-val" presents p-values of the Stock-Wright LM test, presenting weak-instrument-robust inference. The null of this test is that the endogenous regressor is equal to zero. The test is robust to the presence of weak instruments.

*** Significant at the 1 percent level,
** Significant at the 5 percent level,
* Significant at the 10 percent level

Table C-25 ETHNIC INEQUALITY AND ECONOMIC GROWTH—SUB-NATIONAL ESTIMATES, ALL REGIONS, ALTERNATIVE SPECIFICATION OF GDP DYNAMICS, 1992–2012

Dependent variable: Real per capita GRP, $\log(\text{GRP}^{pc})$						
	Lags = 1	Lags = 2	Lags = 3	Lags = 4	Lags = 5	Lags = 6
	(1)	(2)	(3)	(4)	(5)	(6)
Ethnic inequality	-0.0093***	-0.0079***	-0.0078***	-0.0078***	-0.0078***	-0.0079***
	(0.0008)	(0.0008)	(0.0009)	(0.0009)	(0.0009)	(0.0009)
$\log(\text{GRP}^{pc})(t-1)$	0.979***	0.616***	0.568***	0.559***	0.557***	0.554***
	(0.00138)	(0.0111)	(0.0141)	(0.0145)	(0.0148)	(0.0151)
$\log(\text{GRP}^{pc})(t-2)$		0.367***	0.288***	0.268***	0.264***	0.263***
		(0.0109)	(0.0130)	(0.0123)	(0.0125)	(0.0126)
$\log(\text{GRP}^{pc})(t-3)$			0.127***	0.0820***	0.0702***	0.0675***
			(0.0125)	(0.0148)	(0.0151)	(0.0145)
$\log(\text{GRP}^{pc})(t-4)$				0.0741***	0.0490***	0.0348***
				(0.0108)	(0.0108)	(0.0117)
$\log(\text{GRP}^{pc})(t-5)$					0.0434***	0.0174
					(0.0113)	(0.0111)
$\log(\text{GRP}^{pc})(t-6)$						0.0466***
						(0.00988)
Observations	36,452	36,452	36,452	36,452	36,452	36,452
Sub-national Units	2,569	2,569	2,569	2,569	2,569	2,569
R-Squared	0.978	0.981	0.981	0.982	0.982	0.982
F Stat (second)	302198	272866	208520	173426	148628	132767
Country Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Period Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Country-Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Spatial Correlation	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Cluster robust standard errors (on the ADM1 level) are reported in parentheses. The dependent variable is the log of real per capita GRP, measured using data from Leßmann and Seidel (2017). Ethnic inequality is measured as described in Section (2) using differences in nighttime lights across ethnic homelands. The table presents estimates for different specifications of the lag structure. The model specification follows the fully specified FE-OLS model in our benchmark estimates (column 5 of Table C-18), but includes between 1 (column 1) and 6 (column 6) lags of real per capita GDP. All models include country fixed effects, year fixed effects, and country time year fixed effects. The model also account for spatial correlation by including the mean level of real per capita GDP in other regions of the same country, weighted by the inverse distance to the individual region.

*** Significant at the 1 percent level,
** Significant at the 5 percent level,
* Significant at the 10 percent level

Table C-26 ETHNIC INEQUALITY AND ECONOMIC GROWTH—SUB-NATIONAL ESTIMATES, EFFECTS EXCLUDING EUROPEAN REGIONS, 1992–2012

Dependent variable: Real per capita GRP, $\log(\text{GRP}^{pc})$						
	Benchmark		**Country-Year FE**		**Spatial Correlation**	
	FE-OLS (1)	2SLS (2)	FE-OLS (3)	2SLS (4)	FE-OLS (5)	2SLS (6)
	Panel A: Regression results (second stage)					
Ethnic inequality	-0.0245***	-0.0294***	-0.00796***	-0.00840***	-0.00797***	-0.00832***
	(0.0019)	(0.0027)	(0.0009)	(0.0012)	(0.0009)	(0.0012)
$\log(\text{GRP}^{pc})(t-1)$	0.824***	0.823***	0.610***	0.610***	0.610***	0.610***
	(0.0217)	(0.0217)	(0.0139)	(0.0139)	(0.0139)	(0.0139)
$\log(\text{GRP}^{pc})(t-2)$	0.204***	0.204***	0.236***	0.236***	0.237***	0.236***
	(0.0222)	(0.0222)	(0.0128)	(0.0128)	(0.0128)	(0.0128)
$\log(\text{GRP}^{pc})(t-3)$	-0.0531***	-0.0530***	0.0859***	0.0859***	0.0859***	0.0859***
	(0.0104)	(0.0104)	(0.0171)	(0.0171)	(0.0171)	(0.0171)
$\log(\text{GRP}^{pc})(t-4)$	-0.0291***	-0.0299***	0.0515***	0.0515***	0.0515***	0.0515***
	(0.0086)	(0.0086)	(0.0121)	(0.0121)	(0.0121)	(0.0121)
	Panel B: First-stage regression results					
Spatial Instrument	–	0.858***	–	0.824***	–	0.825***
		(0.0237)		(0.0255)		(0.0255)
Observations	32,999	32,999	32,999	32,999	32,999	32,999
Sub-national Units	2,032	2,032	2,032	2,032	2,032	2,032
R-Squared	0.926	0.926	0.983	0.983	0.983	0.983
F Stat (second)	29301	27090	247952	249484	208241	209709
K-P F-Stat (first)	–	1310	–	1042	–	1045
S-Y 10% max IV size	–	16.38	–	16.38	–	16.38
S-W p-val	–	0.000	–	0.000	–	0.000
Country Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Period Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Country-Year Fixed Effects	No	No	Yes	Yes	Yes	Yes
Spatial Correlation	No	No	No	No	Yes	Yes

Notes: Cluster robust standard errors (on the ADM1 level) are reported in parentheses. The dependent variable is the log of real per capita GRP, measured using data from Leßmann and Seidel (2017). Ethnic inequality is measured as described in Section (2) using differences in nighttime lights across ethnic homelands. The table presents estimates from three models, each estimated with the traditional within group estimator (columns labeled “FE-OLS”) and with 2SLS using our spatial instrumental variable. The first model (“Benchmark”) replicates the specification of the country-level dynamic panel data model of Section (3.2), the second specification (“Country-Year FE”) accounts for time-varying unobservables on the country level by including country-year fixed effects. The third specification (“Spatial Correlation”) accounts for spatial correlation between the GRP of sub-national units and a the average of GRP in other sub-national units of the same country, weighted by the inverse of the distance between sub-national units. The row labeled “K-P F-Stat (first)” reports the F-statistic of the Kleibergen-Paap rk Wald test, which is a robust test for weak identification in case the errors are not i.i.d. We also report Stock-Yogo thresholds for the Kleibergen-Paap weak identification test for a demanding critical value of 10% max IV size (labeled “S-Y 10% max IV size”). The row labeled “S-W p-val” presents p-values of the Stock-Wright LM test, presenting weak-instrument-robust inference. The null of this test is that the endogenous regressor is equal to zero. The test is robust to the presence of weak instruments.

*** Significant at the 1 percent level,
** Significant at the 5 percent level,
* Significant at the 10 percent level

Table C-27 ETHNIC INEQUALITY AND ECONOMIC GROWTH—SUB-NATIONAL ESTIMATES, EFFECTS EXCLUDING EUROPEAN AND NORTHERN AMERICAN REGIONS, 1992–2012

Dependent variable: Real per capita GRP, log(GRP^{pc})						
	Benchmark		**Country-Year FE**		**Spatial Correlation**	
	FE-OLS (1)	2SLS (2)	FE-OLS (3)	2SLS (4)	FE-OLS (5)	2SLS (6)
	Panel A: Regression results (second stage)					
Ethnic inequality	-0.0260***	-0.0315***	-0.00797***	-0.00870***	-0.00799***	-0.00862***
	(0.00201)	(0.00291)	(0.000913)	(0.00129)	(0.000912)	(0.00129)
log(GRP^{pc})($t-1$)	0.816***	0.815***	0.613***	0.613***	0.613***	0.613***
	(0.0222)	(0.0222)	(0.0148)	(0.0147)	(0.0148)	(0.0147)
log(GRP^{pc})($t-2$)	0.209***	0.209***	0.235***	0.235***	0.235***	0.235***
	(0.0228)	(0.0227)	(0.0136)	(0.0136)	(0.0135)	(0.0135)
log(GRP^{pc})($t-3$)	-0.0526***	-0.0524***	0.0835***	0.0835***	0.0835***	0.0835***
	(0.0108)	(0.0108)	(0.0181)	(0.0181)	(0.0181)	(0.0180)
log(GRP^{pc})($t-4$)	-0.0304***	-0.0314***	0.0523***	0.0523***	0.0522***	0.0522***
	(0.00910)	(0.00911)	(0.0129)	(0.0129)	(0.0129)	(0.0129)
	Panel B: First-stage regression results					
Spatial Instrument	–	0.880***	–	0.842***	–	0.844***
		(0.0280)		(0.0269)		(0.0268)
Observations	29,392	29,392	29,392	29,392	29,392	29,392
Sub-national Units	1,814	1,814	1,814	1,814	1,814	1,814
R-Squared	0.923	0.923	0.983	0.983	0.983	0.983
F Stat (second)	24611	22528	218489	217442	183599	182818
K-P F-Stat (first)	–	1260	–	983	–	987
S-Y 10% max IV size	–	16.38	–	16.38	–	16.38
S-W p-val	–	0.000	–	0.000	–	0.000
Country Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Period Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Country-Year Fixed Effects	No	No	Yes	Yes	Yes	Yes
Spatial Correlation	No	No	No	No	Yes	Yes

Notes: Cluster robust standard errors (on the ADM1 level) are reported in parentheses. The dependent variable is the log of real per capita GRP, measured using data from Leßmann and Seidel (2017). Ethnic inequality is measured as described in Section (2) using differences in nighttime lights across ethnic homelands. The table presents estimates from three models, each estimated with the traditional within group estimator (columns labeled "FE-OLS") and with 2SLS using our spatial instrumental variable. The first model ("Benchmark") replicates the specification of the country-level dynamic panel data model of Section (3.2), the second specification ("Country-Year FE") accounts for time-varying unobservables on the country level by including country-year fixed effects. The third specification ("Spatial Correlation") accounts for spatial correlation between the GRP of sub-national units and a the average of GRP in other sub-national units of the same country, weighted by the inverse of the distance between sub-national units. The row labeled "K-P F-Stat (first)" reports the F-statistic of the Kleibergen-Paap rk Wald test, which is a robust test for weak identification in case the errors are not i.i.d. We also report Stock-Yogo thresholds for the Kleibergen-Paap weak identification test for a demanding critical value of 10% max IV size (labeled "S-Y 10% max IV size"). The row labeled "S-W p-val" presents p-values of the Stock-Wright LM test, presenting weak-instrument-robust inference. The null of this test is that the endogenous regressor is equal to zero. The test is robust to the presence of weak instruments.

*** Significant at the 1 percent level,
** Significant at the 5 percent level,
* Significant at the 10 percent level

Table C-28 ETHNIC INEQUALITY AND ECONOMIC GROWTH—SUB-NATIONAL ESTIMATES, EFFECTS FOR ASIAN REGIONS, 1992–2012

Dependent variable: Real per capita GRP, $\log(\mathrm{GRP}^{pc})$

	Benchmark		**Country-Year FE**		**Spatial Correlation**	
	FE-OLS (1)	2SLS (2)	FE-OLS (3)	2SLS (4)	FE-OLS (5)	2SLS (6)
	Panel A: Regression results (second stage)					
Ethnic inequality	-0.0354***	-0.0450***	-0.0062***	-0.0083***	-0.0063***	-0.0082***
	(0.0047)	(0.0072)	(0.0016)	(0.0022)	(0.0016)	(0.0022)
$\log(\mathrm{GRP}^{pc})(t-1)$	0.853***	0.853***	0.539***	0.540***	0.539***	0.540***
	(0.0107)	(0.0107)	(0.0198)	(0.0198)	(0.0198)	(0.0198)
$\log(\mathrm{GRP}^{pc})(t-2)$	0.225***	0.225***	0.261***	0.261***	0.261***	0.261***
	(0.0125)	(0.0125)	(0.0187)	(0.0187)	(0.0187)	(0.0187)
$\log(\mathrm{GRP}^{pc})(t-3)$	-0.113***	-0.113***	0.117***	0.117***	0.117***	0.117***
	(0.0142)	(0.0142)	(0.0268)	(0.0268)	(0.0268)	(0.0268)
$\log(\mathrm{GRP}^{pc})(t-4)$	-0.0137	-0.0140	0.0599***	0.0600***	0.0599***	0.0600***
	(0.0112)	(0.0111)	(0.0178)	(0.0178)	(0.0178)	(0.0178)
	Panel B: First-stage regression results					
Spatial Instrument	–	0.833***	–	0.807***	–	0.808***
		(0.0308)		(0.0335)		(0.0335)
Observations	13,851	13,851	13,851	13,851	13,851	13,851
Sub-national Units	846	846	846	846	846	846
R-Squared	0.920	0.920	0.976	0.976	0.976	0.976
F Stat (second)	27136	25094	70196	66198	58670	55331
K-P F-Stat (first)	–	731	–	581	–	582
S-Y 10% max IV size	–	16.38	–	16.38	–	16.38
S-W p-val	–	0.000	–	0.000	–	0.000
Country Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Period Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Country-Year Fixed Effects	No	No	Yes	Yes	Yes	Yes
Spatial Correlation	No	No	No	No	Yes	Yes

Notes: Cluster robust standard errors (on the ADM1 level) are reported in parentheses. The dependent variable is the log of real per capita GRP, measured using data from Leßmann and Seidel (2017). Ethnic inequality is measured as described in Section (2) using differences in nighttime lights across ethnic homelands. The table presents estimates from three models, each estimated with the traditional within group estimator (columns labeled "FE-OLS") and with 2SLS using our spatial instrumental variable. The first model ("Benchmark") replicates the specification of the country-level dynamic panel data model of Section (3.2), the second specification ("Country-Year FE") accounts for time-varying unobservables on the country level by including country-year fixed effects. The third specification ("Spatial Correlation") accounts for spatial correlation between the GRP of sub-national units and a the average of GRP in other sub-national units of the same country, weighted by the inverse of the distance between sub-national units. The row labeled "K-P F-Stat (first)" reports the F-statistic of the Kleibergen-Paap rk Wald test, which is a robust test for weak identification in case the errors are not i.i.d. We also report Stock-Yogo thresholds for the Kleibergen-Paap weak identification test for a demanding critical value of 10% max IV size (labeled "S-Y 10% max IV size"). The row labeled "S-W p-val" presents p-values of the Stock-Wright LM test, presenting weak-instrument-robust inference. The null of this test is that the endogenous regressor is equal to zero. The test is robust to the presence of weak instruments.

*** Significant at the 1 percent level,
** Significant at the 5 percent level,
* Significant at the 10 percent level

Table C-29 ETHNIC INEQUALITY AND ECONOMIC GROWTH—SUB-NATIONAL ESTIMATES, EFFECTS FOR LATIN AMERICAN REGIONS, 1992–2012

Dependent variable: Real per capita GRP, log(GRP^{pc})						
	Benchmark		**Country-Year FE**		**Spatial Correlation**	
	FE-OLS (1)	2SLS (2)	FE-OLS (3)	2SLS (4)	FE-OLS (5)	2SLS (6)
	Panel A: Regression results (second stage)					
Ethnic inequality	-0.0125***	-0.0184***	-0.0040***	-0.0041**	-0.0041***	-0.0044**
	(0.0017)	(0.0031)	(0.0011)	(0.0017)	(0.0011)	(0.0017)
log(GRP^{pc})$(t-1)$	1.108***	1.105***	0.697***	0.697***	0.695***	0.695***
	(0.0149)	(0.0148)	(0.0260)	(0.0258)	(0.0260)	(0.0259)
log(GRP^{pc})$(t-2)$	-0.185***	-0.184***	0.269***	0.269***	0.269***	0.269***
	(0.0249)	(0.0249)	(0.0298)	(0.0298)	(0.0298)	(0.0298)
log(GRP^{pc})$(t-3)$	0.0727***	0.0724***	0.0847***	0.0848***	0.0855***	0.0856***
	(0.0253)	(0.0253)	(0.0215)	(0.0214)	(0.0215)	(0.0215)
log(GRP^{pc})$(t-4)$	-0.0245*	-0.0253*	-0.0600***	-0.0599***	-0.0584***	-0.0581***
	(0.0133)	(0.0134)	(0.0144)	(0.0145)	(0.0145)	(0.0146)
	Panel B: First-stage regression results					
Spatial Instrument	–	0.864***	–	0.832***	–	0.833***
		(0.0735)		(0.0788)		(0.0787)
Observations	4,984	4,984	4,984	4,984	4,984	4,984
Sub-national Units	300	300	300	300	300	300
R-Squared	0.972	0.972	0.996	0.996	0.996	0.996
F Stat (second)	56636	58422	155561	156167	129641	130363
K-P F-Stat (first)	–	138	–	111	–	112
S-Y 10% max IV size	–	16.38	–	16.38	–	16.38
S-W p-val	–	0.000	–	0.000	–	0.000
Country Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Period Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Country-Year Fixed Effects	No	No	Yes	Yes	Yes	Yes
Spatial Correlation	No	No	No	No	Yes	Yes

Notes: Cluster robust standard errors (on the ADM1 level) are reported in parentheses. The dependent variable is the log of real per capita GRP, measured using data from Leßmann and Seidel (2017). Ethnic inequality is measured as described in Section (2) using differences in nighttime lights across ethnic homelands. The table presents estimates from three models, each estimated with the traditional within group estimator (columns labeled "FE-OLS") and with 2SLS using our spatial instrumental variable. The first model ("Benchmark") replicates the specification of the country-level dynamic panel data model of Section (3.2), the second specification ("Country-Year FE") accounts for time-varying unobservables on the country level by including country-year fixed effects. The third specification ("Spatial Correlation") accounts for spatial correlation between the GRP of sub-national units and a the average of GRP in other sub-national units of the same country, weighted by the inverse of the distance between sub-national units. The row labeled "K-P F-Stat (first)" reports the F-statistic of the Kleibergen-Paap rk Wald test, which is a robust test for weak identification in case the errors are not i.i.d. We also report Stock-Yogo thresholds for the Kleibergen-Paap weak identification test for a demanding critical value of 10% max IV size (labeled "S-Y 10% max IV size"). The row labeled "S-W p-val" presents p-values of the Stock-Wright LM test, presenting weak-instrument-robust inference. The null of this test is that the endogenous regressor is equal to zero. The test is robust to the presence of weak instruments.

*** Significant at the 1 percent level,
** Significant at the 5 percent level,
* Significant at the 10 percent level

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