The Persistent Effect of the African Slave Trades on Development: Difference-in-difference evidence

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Introduction

- A majority of the world's poorest countries are in Africa
- The continent also exhibits high income inequality within and across countries
- Can the long-run effects of the African slave trades help explain poverty and inequality in Africa?

Nunn (2008)

- Nunn (2008) first attempted to quantify the long-run effects of the slave trades
- Constructed estimates of the number of slaves taken from each country in Africa (in 2000) from shipping records
- Nunn (2008) regresses log GDP/capita on the log of the slaves exported from each country normalized by its area, instrumented by distance to slave ports
    - The estimated effect on cross-country income differences is large and statistically significant
    - A one log point increase is slave exports/area is estimated to reduce real per capita GDP by over 0.2 log points
    - Ignoring the IV, a one standard deviation decrease in the log of slave exports per capita is associated with about a 50% increase in GDP/capita

Nunn (2008)

- Nunn (2008) has two major limitations
- The first is with identification
  - The first stage F-stat is < 5
    - Staiger-Stock rule of thumb cutoff for weak instruments is 10
  - The IV is distance to areas where demand for slaves was high
    - But this also captures areas that are close to important ports which may affect other forms of trade
- The second is in isolating the channel of causality
  - Nunn (2008) estimates the total average effect
  - This suggests the legacy of the slave trades remains economically important, but provides little evidence as to why

Nunnand Wantchekon (2011)

- Nunn and Wantchekon (2011) examine the channels through which the legacy of the slave trades continues to affect economic development
- Link Afrobarometer survey data to ethnic level slave trade data
- Individuals in ethnic groups that historically engaged in the trans-Atlantic or Indian slave trades report lower levels of trust today
- Suggests that cultural channels of transmission are important
- But Nunn and Wantchekon aren't able to estimate the economic importance of these effects

Contributions

- I leverage variation in the persistence of ethnic groups to estimate the long-run effect of the African slave trades
- The primary contributions are to the literature on the slave trades:
  1. The identification strategy is distinct from prior studies
  2. The estimated effect can be attributed entirely to the cultural effects of the slave trades
  3. Estimates are at the sub-national (and pre-colonial) level that shaped the slave trades
- This paper also contributes to the literature on social capital
  - I study large and plausibly exogenous variation in social capital
  - Results suggest that shocks to social capital are extremely persistent and economically important

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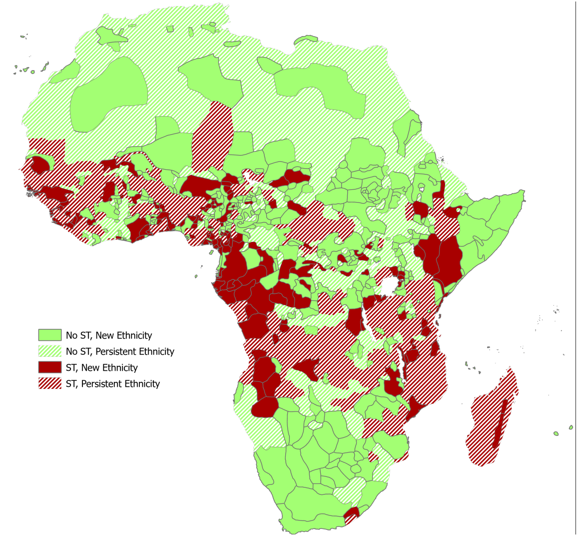
Data

- Pre-colonial ethnic boundaries
  - Originally from Murdock (1959), digitized by Nunn (2008), and obtained from the replication data for Nunn and Wantchekon (2011)
  - Boundaries of ethno-linguistic groups in Africa in the late 19th century
- Contemporary ethnic boundaries
  - Felix and Meur (2001), digitized by the Harvard AfricaMap project
- Luminosity (nighttime light) data Figure Table
  - VIIRS Stray Light Connected Day/Night Band Composites (NOAA)
  - 15 arc second spatial resolution
  - Post processing in the Google Earth Engine
  - Annual averages for 2014-2018 to reduce noise (e.g. business cycles)
- Population
  - LandScan (Oak Ridge National Laboratory)
  - Produced annually, 15 arc second resolution
- Controls for temperature suitability for P. falciparum and P. vivax malaria, gold, diamond and oil reserves, rainfall, and the number of neighbors in the Murdock boundary data

Ethnic boundaries: slave trade participation and persistence



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Empirical Strategy

I estimate the difference-in-difference specification

$$Y_{it} = \alpha_t + \beta_0 ST_i + \beta_1 PERS_i + \gamma ST_i \times PERS_i + \lambda' X_i + \epsilon_{it}$$

where

- Y_{it} log of GDP (or GDP/capita) measured in pre-colonial ethnic boundary i in year t
- α_t are year fixed-effects
- ST_i is an indicator denoting participation in the slave trade
- $PERS_i$ is an indicator denoting ethnic group persistence
- X_i is a vector of control variables
- γ is the difference-in-difference estimate of the long-run effect of slavery on economic development
- All estimates report spatial HAC standard errors that are robust to serial correlation across time and arbitrary spatial correlation within a 1,500 km radius (Conley, 1999, 2016) Details

Identifying Assumption

Parallel trends

Absent the slave trades, the difference in long-run productivity between areas where the pre-colonial ethnic group persisted versus those where it did not persist would not be larger in areas that participated in the slave trade relative to those that did not.

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OLS results are unstable given controls

	(1) log($GDP/capita$)	(2) log(GDP)	(3) log($GDP/capita$)	(4) log(GDP)
Slave trade	-0.364***	0.108	-0.063	0.390***
	(0.058)	(0.081)	(0.063)	(0.071)
Controls	NO	NO	YES	YES
Time FE	Yes	Yes	Yes	Yes
Observations	4,175	4,175	4,175	4,175

Spatial HAC standard errors in parenthesis (Conley, 1999, 2016). * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$
The dependent variable in columns (1) and (3) is the log of GDP/capita estimated using the log of night lights per capita measured using VIIRS luminosity data. In columns (2) and (4), the log of GDP is the dependent variable and is estimated using the log of night lights. All variables are calculated over the historical ethnic boundaries presented in Murdock (1959). The variable "Slave trade" is an indicator recording whether the ethnic group historically participated in the slave trade.

Difference-in-difference estimates show a large and statistically significant effect

	(1) log($GDP/capita$)	(2) log(GDP)	(3) log($GDP/capita$)	(4) log(GDP)
Slave trade	-0.255***	0.097	0.054	0.424***
	(0.074)	(0.105)	(0.086)	(0.088)
Persistent ethnicity	0.467***	0.653***	0.337***	0.426***
	(0.103)	(0.106)	(0.078)	(0.067)
Slave trade x Persistent	-0.334***	-0.149	-0.329***	-0.202*
Time FE	Yes	Yes	Yes	Yes
Observations	4,175	4,175	4,175	4,175

Spatial HAC standard errors in parenthesis (Conley, 1999, 2016). * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$
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Results

- The difference-in-difference estimate is robust to:
  - Predicted persistence from variables independent of the slave trades in place of actual persistence
  - The use of raw night lights data in place of GDP estimates
  - Aggressively winsorizing the log of GDP/capita (5th and 95th percentiles)

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Conclusion

- The African slave trades continue to have a large effect on development
    - The large effect detected through cultural channels indicates that most, if not all, of the long-run effects are driven by reduced social capital
- This research suggests that shocks to social capital are extremely persistent
    - From a public policy perspective, this suggests that responding aggressively to shocks to social capital may be important

Future research

- Can interventions improve social capital?
  - Finding ways to bolster trust, instead of just wealth, may have high economic returns
- What are the long-run dynamics of shocks to social capital?
  - This paper suggests that shocks can be long lasting. Is that externally valid?
  - What is the specific autoregressive process?

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Luminosity: Map of Africa

Figure: Night lights by pre-colonial ethnic boundary

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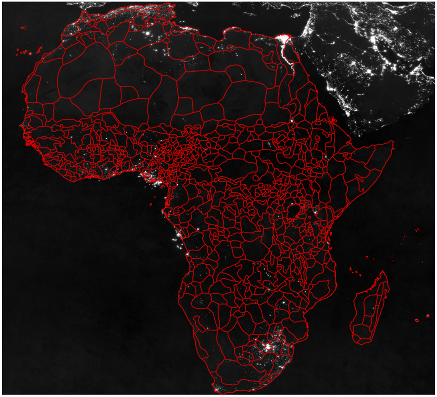

Figure 1 plots the log of 2014 luminosity readings on pre-colonial ethnic boundaries. Night light data is from the Visible Infrared Imaging Radiometer Suite (VIIRS) Day/Night Band (DNB). Night lights values were constructed using the Google Earth Engine beginning with stray light corrected monthly composites. The median pixel value across each reading from 2014 was then taken. I then plotted the natural log of 1 plus each pixel value.

Luminosity: Fit to GDP

	(1) log(*GDP*)	(2) log(*GDP* / *capita*)
Night lights	0.666***	0.719***
	(0.073)	(0.102)
2015	-0.039	-0.005
	(0.189)	(0.065)
NL x 2015	-0.007	-0.040
	(0.022)	(0.045)
2016	0.147	0.095**
	(0.124)	(0.041)
NL x 2016	0.012	0.049
	(0.016)	(0.040)
2017	-0.896***	-0.156
	(0.316)	(0.158)
NL x 2017	0.018	-0.191**
	(0.037)	(0.087)
2018	-0.935***	-0.142
	(0.326)	(0.170)
NL x 2018	0.027	-0.185*
	(0.038)	(0.094)
Adj R^2	0.660	0.396
Entities	48	48
Time periods	5	5

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Spatial HAC standard errors

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Let S_{it} denote an observation and define

$$K_N\left(S_{it}, S_{jk}\right) = \begin{cases} 0 & i \neq j \wedge t \neq k \\ 1 & i = j \wedge t \neq k \\ 0 & d(S_{it}, S_{jk}) > 1,500 \wedge t = k \\ 1 & d(S_{it}, S_{jk}) \leq 1,500 \wedge t = k \end{cases} \tag{1}$$

where $d(S_{it}, S_{jk})$ denotes the distance, in kilometers, between the centroids of the two observations. Under the assumption that observations further than $1,500$ km from each other are not spatially correlated, Conley (1999) and Conley (2016) show that the asymptotic distribution of $\hat{\beta}$, where β is the population vector of regression coefficients and $\mathbf{x_{it}}$ is a vector of covariates, is given by

$$\hat{\beta} \overset{A}{\sim} \mathcal{N}\left(\beta, \frac{1}{TN}\left(\frac{1}{TN}\sum_{i=1}^{N}\sum_{t=1}^{T}\mathbf{x_{it}}\mathbf{x_{it}}'\right)^{-1} \hat{V}_N \left(\frac{1}{TN}\sum_{i=1}^{N}\sum_{t=1}^{T}\mathbf{x_{it}}\mathbf{x_{it}}'\right)^{-1}\right) \tag{2}$$