Legal Origin from Outer Space (and on Foot): A Geographic Regression Discontinuity Approach

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Abstract

This article advances the debate over legal origins by using survey data and satellite imagery to measure economic development and by employing a geographic regression discontinuity (GRD) design to take into account climate, culture, and other observable and unobservable factors correlated with location. The basic legal structure of most countries was imposed by colonial powers, but Great Britain, France and other European nations did not colonize randomly. The lack of random assignment means that simple cross-country analyses may lead to erroneous conclusions because of unobservables correlated with legal origin. GRD is especially promising for Africa because many borders were drawn in Europe by diplomats and bureaucrats who had only the haziest knowledge of local conditions, except in coastal areas. As a result, borders split ethnic groups, and areas on either side of the border are similar along observable dimensions and presumably on unobservable ones as well. Satellite imagery is used to measure nighttime lights. Survey data are used to measure individual height and whether a household has electricity, a cell phone, a non-dirt floor, non-human-powered transport, or access to improved latrines or toilets. The regression coefficients are of mixed signs. The point estimates thus suggest that countries with common law legal origin do not perform consistently better, as measured by

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these eight proxies for economic development, than those with civil law. Most coefficients are not statistically significant at conventional levels, although the most robust of those that are – non-human-powered transport and light per capita – show a civil law advantage. Nevertheless, because the confidence intervals are wide, we cannot exclude a positive common law effect for most outcomes.

1 Introduction

This article advances the debate over legal origins by taking into account the non-random way legal regimes were spread. The basic legal structure of most countries was imposed by colonial powers, but Great Britain, France and other European nations did not colonize randomly. Britain was the dominant world power from at least the mid-eighteenth century, and it used that power to colonize many of the places that were most promising from an economic perspective. It is not a coincidence that the British took control of South Africa's vast mineral wealth (even though most of the country was initially colonized by the Dutch), while France colonized the Sahara, including countries that are today Mauritania, Mali, Niger, and Chad. The lack of random assignment of colonies to European powers means that simple cross-country analyses may lead to erroneous conclusions because of unobservables correlated with legal origin.

This article takes into account the non-random character of the colonization process by adopting a geographic regression discontinuity approach and by focusing on Africa. While the colonization process was not random, the borders between African colonies and their successor states were largely arbitrary. The great powers drew most borders with only the haziest knowledge of local conditions, except in coastal areas. The borders they drew were often straight lines (as between Mozambique and Zambia) or followed natural features (such as lakes or watersheds). Such boundaries resulted in relatively similar geographic and climatic conditions on both sides of the border. In addition, the boundary lines often split ethnic groups, which meant that the two sides of the border were usually similar culturally as well as in their climate and geography. It is thus plausible to consider the location of the border as exogenous. By focusing on areas close to the border and by analyzing whether and how economic conditions change at the border, one can therefore identify the effect of colonial policies, including law, while holding geography, climate, and culture constant.

Geographic regression discontinuity analysis of legal origin is made possible by fine-grained data from two sources: satellite imagery that maps economic activity in roughly one square kilometer units and geolocated survey data. For about a decade, economists and other social scientists have been using satellite images of nighttime light as a proxy for economic development: the more light detected, the more economic activity. This proxy is especially powerful for Africa, where a key indicator of economic development is the provision and use of electricity: a village with no electrical power will ordinarily be dark at night; a village where only a few rich households have lights will be dim, but a village where nearly everyone has electricity will be relatively bright.

For the last three decades, USAID (The United States Agency for International Development) has conducted detailed Demographic and Health Surveys (DHS) of most African countries. Respondents were interviewed in person, and "biomarkers," including height, were measured directly. While these surveys focus on health, they contain a wealth of information of economic relevance, including measures of household consumption such as whether a household had electricity, an improved latrine or toilet, a cell phone, a non-dirt floor, or non-human-powered transport (such as a car, motorcycle, or boat) (Min et al., 2013).We focus some of our analysis on height, primarily female height, which is a good proxy for nutrition and health in the first two years of life. Height is particularly revealing because it is determined primarily by nutrition in the first two years of life; so if one restricts analysis to people who were born two or more years before independence, height provides insight into colonial conditions.

Using survey data and nighttime light as proxies for economic activity not only provides the high-resolution data necessary for geographic regression discontinuity analysis, but it also makes it unnecessary to rely on official, government-generated economic statistics, which are notoriously inaccurate for low-income countries, including most African nations. A further advantage of using survey data and nighttime lights as the primary dependent variables is that there are a wealth of other data that are available on a fine-grained geographic basis. These data include information on climate (such as temperature and rainfall), geography (whether the terrain is flat or rugged), and ethnicity (”tribe”). By using these data, we can confirm that conditions on both sides of the relevant borders are indeed similar, and, where they are not, can control for differences or exclude borders that lack covariate balance.

The debate over legal origins is important because the literature has provided “a blueprint for policy reform” (La Porta, Lopez-de Silanes and Shleifer, 2008, p. 323). The finding that common law countries generally did better supplied an important argument for the World Bank and other institutions to encourage all countries to adopt policies with the features they saw as best in the common law tradition. Shleifer and his co-authors argued, “the direction of such reforms is simply less government intervention” (La Porta, Lopez-de Silanes and Shleifer, 2008, p. 324). In addition, the debate over legal origins implicates fundamental questions about the importance of history, institutions, geography, and colonization. For both theoretical and policy reasons, it is important to understand the relationship, if any, between legal origin and economic performance.

Our results suggest no consistent effect of legal origin on economic development or well being. For three variables – Light, Sanitation, and Cell Phone –, the regression coefficients usually show a common-law advantage, although the coefficients are only sometimes statistically significant at the conventional levels (p-values less than 0.05). For four variables – Light per Capita, Electricity, Height, and Transport – civil law countries seem to perform better. For two of these variables – Light per Capita and Transport – the p-values are less than 0.05 in both the preferred specification and nearly all of the robustness checks. The sign on Floor is negative in our preferred specification, but this result is not robust.

2 Literature

2.1 Legal Origin

Starting in the late 1990s, an important literature in economics has documented pervasive correlations between economic outcomes, legal rules, and legal origin. In this literature, legal origin means whether a country's legal system is based on British common law, or French, German, or Scandinavian civil law (La Porta, Lopez-de Silanes and Shleifer, 2008). This literature argued that common law countries had better protection for investors and therefore larger capital markets, freer labor markets and therefore lower unemployment, better guarantees of judicial independence and therefore stronger property rights. The source of the common law advantage was either the flexibility derived from greater judicial discretion or the purportedly greater support the common law provided for free markets. Critics, however, pointed out that the principal articles in this literature miscoded key variables, including variables measuring the extent of investor protection and legal origin itself (Spamann, 2010; Klerman et al., 2011).

One strand of the legal-origin literature analyzed economic growth as its dependent variable. Mahoney (2001) showed that common law countries, on average, had higher GDP growth. Klerman et al. (2011) confirmed that finding, but argued that the superior performance of common law countries could be better explained by non-legal colonial policies, such as education. It also suggested, but could not definitively demonstrate that the common law advantage might reflect the non-random character of colonization, a hypothesis explored in this paper.

A recent article Anderson (2018), like this one, uses a regression discontinuity approach to analyze the effect of legal origin in sub-Saharan Africa. It concludes that the common law's weaker protection for female marital property rights led to higher rates of HIV infection. Like this paper, Anderson (2018) uses USAID survey data, and, in fact, we learned about this powerful survey dataset from Anderson's work. We are unaware of any papers that use nighttime lights to analyze legal origin or that use any other USAID survey data for that purpose.

2.2 Comparative Colonialism

The debate over legal origin is, at least in Africa, part of a long-standing debate about differences between colonial powers. Although Portugal and Belgium also had significant colonies in Africa, most of the debate has been about British and French colonialism and has focused on West Africa, where British and French colonies existed in close proximity. Early literature stressed differences in governance. The British formally adopted a policy of "indirect rule," which meant that they governed through existing chiefs and sought to "conserve what was good in indigenous institutions and [to] assist them to develop along their own lines" (Crowder, 1964, p. 198). While the French also ruled through chiefs, they undermined traditional authority by selecting as chiefs those who had learned French and had "rendered services to the French cause." Chiefs in French colonies were "reduced to . . . a mouthpiece for orders emanating from outside" (Crowder, 1964, p.200). The French policy was initially to "assimilate" Africans to French culture and governance. Although the policy of "assimilation" was replaced with a policy of "association," even that newer policy had tendencies that aimed to teach Africans how to be good Frenchmen (Crowder, 1964, pp.200-202). Crowder's view on the differences between French and British colonial governance was challenged by those who argued that, in practice, the two colonizers were indistinguishable. According to this revisionist account, by necessity, the French relied on traditional chiefs, and, in fact, the policy of "association" was very close to the British practice of indirect rule (Deshamps, 1963).

Even those, such as Crowder (1968), who stressed differences between the French and British politically, saw little difference between the two colonial powers in the economic sphere. Both French and British colonies were "subjected to an administrative system whose avowed purposes were to bring the material as well as the spiritual 'benefits' of Europe to the African, but saw these not in terms of the rational development of these colonies in their own interest, but in the interest of the mother country" (Crowder, 1968, p.274).

A more recent strand of scholarship has taken a different approach and seems to conclude that British colonialism had better economic effects. Asiwaju (1976), Miles (1994), and Welch Jr. (1966) devoted entire monographs to a single ethnic group that had been divided by colonial and modern boundaries. Asiwaju (1976) examined the Yoruba, who straddle the border that is currently between Nigeria and Benin. Miles (1994) studied the Hausa, who live on both sides of the boundary between modern Nigeria and Niger. Welch Jr. (1966)) studied the Ewe, who were split between British and French colonies in lands now ruled by Ghana, Togo, and Cameroon. All three authors found that those who lived on the British side of the border did much better economically. For the Hausa, Miles (1994, p. 184) found, "whereas the British encouraged indigenous cultivation through free labor, the French implemented state control of production with compulsory cultivation." The resulting differences in economic growth led Hausa to consider villages on the Nigerian (British) side as "incarnating . . . wealth and good fortune," while viewing those on the French side as places of "suffering and poverty" Miles (1994, p. 176). For the Yoruba, Asiwaju similarly concluded:

> The history of Western Yorubaland under colonial rule bore out the wisdom shown in the policy arguments of the British in West Africa, arguments that recall those of Adam Smith in support of free against slave labour; that in the development and exploitation of the sylvan and agricultural resources of colonies, indigenous cultivation should be preferred to controlled production as a method (Asiwaju, 1976, p. 173).

Of course, while this recent strand of literature tends to find that British colonialism had superior (or at least less deleterious) economic consequences, its hallmark is intensive study of relatively small areas. It would be improper to generalize to all of Africa based on three studies, all of which relate to Western Africa. In addition, these studies do not attribute economic differences to characteristics most often associated with the contrast between common and civil law. They emphasize the negative effects of forced labor and the benefits of liberal trading policies, rather than the effects of precedent, juries, or codes. On the other hand, the differences highlighted by Miles (1994), Asiwaju (1976), and Welch Jr. (1966) accord with La Porta, Lopez-de Silanes and Shleifer (2008, p. 286)'s "broad conception of legal origin as a style of social control of economic life [where] common law stands for the strategy of social control that seeks to support private market outcomes, whereas civil law seeks to replace such outcomes with state-desired allocations."

The conclusions of this more recent literature, which is historical and ethnographic in character, have been only partially confirmed by quantitative approaches. Bertocchi and Canova (2002) employed a cross-country regression approached and found that former British colonies in Africa grew faster than former French colonies. In contrast, Bubb (2013) analyzed adjacent areas of Ghana (a former British colony) and the Cote d'Ivoire (a former French colony) using regression discontinuity analysis. He found little difference between the strength of property rights near the border, even though formal law in Cote d'Ivoire provided stronger protection. To the extent that there were differences in property rights, they were explained by soil suitability for cocoa production, a high value export crop. Areas suitable for cocoa developed stronger property rights, in accordance with Demsetz's (1967) theory that increases in land value lead to stronger property rights institutions. Bubb's work shares with this paper the use of regression discontinuity analysis to control for unobservable local variations, and his finding that soil quality was more important than law echoes the conclusion of this paper that, once one controls for geography and the non-random character of the colonization process, legal origin has little explanatory power.

3 Data and Methods

3.1 Data and Case Selection

This project combines geographic information, satellite data, survey data, and ethnicity maps with legal and colonial origin data. These data come from a variety of sources and allow us to test the effect of legal and colonial origins on contemporary economic development.

3.1.1 Nighttime Satellite Data

The research design for our study requires fine-grained spatial data to measure economic development and geographic variables. The nighttime satellite data comes from NOAA's National Centers for Environmental Information Earth Observation Group (National Centers for Environmental Information Earth Observation Group, 2019). In 1961, the U.S. Defense Department set up the Defense Meteorological Satellite Program (DMSP) to provide weather information for military purposes. In the early years, the key motivation for the program was the desire to predict cloud cover and other weather-related phenomena that would interfere with reconnaissance photography of America's Cold War nuclear adversaries, Russia and China (Hall, 2001). While the system was primarily designed to detect clouds, the Operational Linescan System (OLS) produced fine-grained data on the amount of light emitted from the ground between 8:30 and 10:00 PM (Michalopoulos and Papaioannou, 2013, p. 120). In 1992, data collected from the satellites was declassified and made available to the scientific community. In 1998, control and maintenance of the satellites was transferred to the National Oceanic and Atmospheric

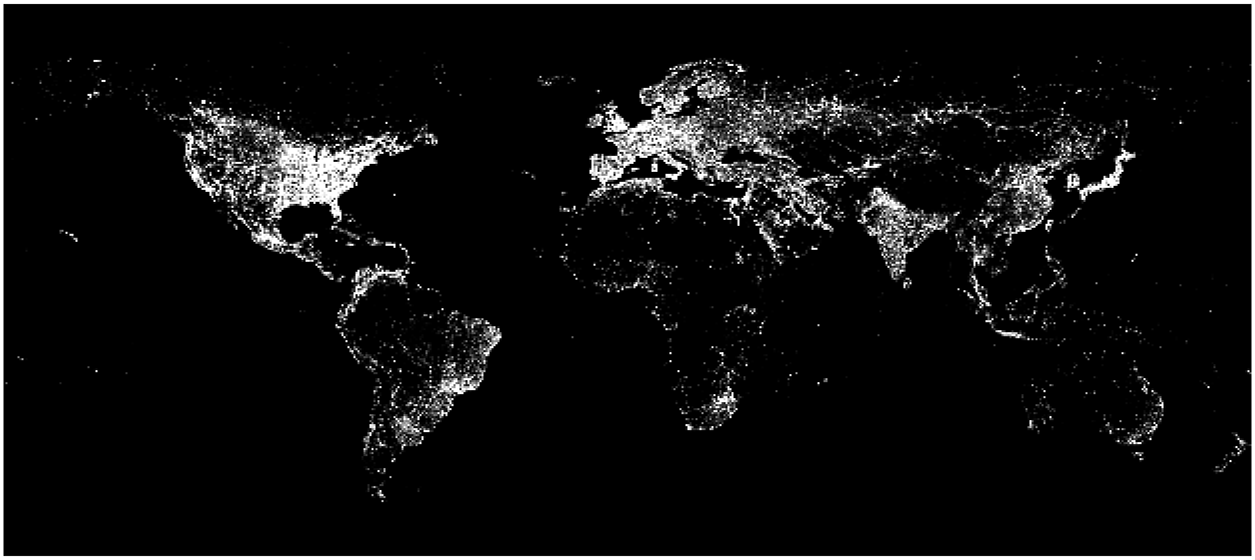
Administration (NOAA) (Air, 2017). Light density is measured as an integer between zero and 63. For less developed countries, the main contrast is between pixels with value zero (minimal light) and 1-10 (some light). In major cities in developed countries, maximal values (63) are not uncommon.[1]

Starting in with Paul Sutton and Robert Costanza's pioneering 2002 article, researchers have realized that these satellite nighttime light data could be used to estimate economic activity, especially if corrections were made to account for clouds, lightning, forest fires, gas flares, and similar phenomena (Sutton and Costanza, 2002, p. 512). In fact, nighttime lights have two significant advantages over official government GDP and related statistics. First, official GDP figures can be unreliable, especially in the developing world, where governments often lack the money and expertise to produce high quality statistics. Second, GDP numbers are usually compiled and published on a national basis, or, at best, at the level of large subnational governmental units, like Canadian provinces or U.S. states. In contrast, the nighttime light data are published at 30 arc second resolution. 30 arc seconds is half an arc minute, and 60 arc minutes make a degree of longitude or latitude. Therefore, near the equator, a resolution of 30 arc seconds is about one square kilometer. Away from the equator, 30 arc second resolution covers a somewhat smaller area. The ability to map economic activity at such a fine resolution makes it possible to analyze local phenomena and to perform the geographic regression discontinuity approach employed in this paper.

[1] The current iteration of the paper relies on DMSP data that has been recalibrated . Subsequent versions of the paper will make use of data from the Visible Infrared Imaging Radiometer Suite (VIIRS) instrument from the Suomi National Polar Partnership (SNPP) satellite launched jointly by NASA and NOAA in 2011.

The map below shows the global distribution of nighttime lights in 1994-95:

Figure 1: Distribution of Global Nighttime Lights



Source: `https://eoimages.gsfc.nasa.gov/images/imagerecords/55000/55167/earth_lights.gif`

The correlation between economic activity and night lights is readily apparent. The eastern US, Europe, Japan, and coastal China are brightly lit. In contrast, the rocky mountain American west, non-coastal South America, and northwest Asia are significantly dimmer. The contrast between North and South Korea is particularly instructive. South Korea looks like an island due north of the southwestern tip of Japan. The land connecting South Korea to Russia is North Korea, which is at a relatively low level of economic development, and is thus dark and invisible. Differences in population density cannot account for the darkness of North Korea, because North Korea is more densely populated than Spain or France, both of which are clearly visible. In the map above, Africa seems to be almost entirely dark, but if one focuses just on Africa, differences within Africa emerge, as in the map below.

High levels of economic activity along the Nile (upper right), in South Africa, and in

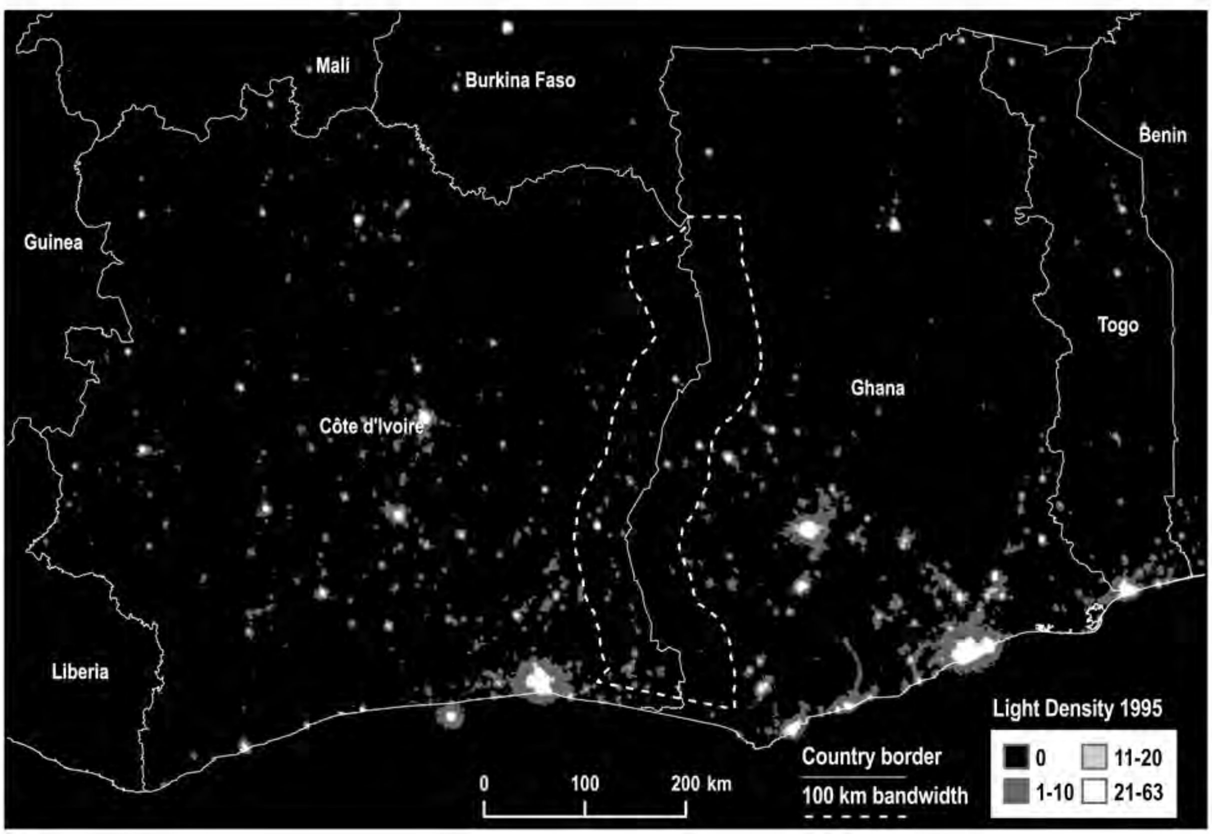
Figure 2: Distribution of Africa Nighttime Lights

Source: https://eoimages.gsfc.nasa.gov/images/imagerecords/55000/55167/earth_lights.gif

parts of coastal West Africa stand out, while the Sahara is almost entirely dark. Of course, the use of nighttime lights is not without its own problems. Light data measure aggregate economic activity, so without good data on population, they cannot be used to measure activity per capita. Light data also primarily measure the extent to which a population uses electric lights. That has proved to be a useful proxy for economic activity for low and moderate income countries, but for rich countries, increases in GDP do not correlate with greater use of electric lights. Nevertheless, because this paper focuses on Africa, measuring the extent of electrification is a very useful proxy for economic growth, and, by many accounts, more reliable than official government statistics.

Because this paper focuses on borders, it is helpful to zoom in further. Figure 3 shows nighttime lights in Ghana, Cote-d'Ivoire and neighboring regions. Most of these areas are dark, but a few bright spots (cities) are visible. Fainter spots usually indicate small cities or villages with electricity. Of greatest interest is the area near the border between the Cote d'Ivoire and Ghana. The dotted lines show a 100 kilometer bandwidth (50 kilometers on each side of the border).[2] Cote d'Ivoire is a former French colony whose legal system is founded upon civil law. Ghana is a former British colony whose legal system is usually classified as common law. Most of the area near the border is dark, but the area on the Cote d'Ivoire (civil law) side is a little brighter.

Figure 3: Nighttime Lights in the Ghana-Cote d'Ivoire Region, 1995



[2]As discussed below, the 20 km closest to the ocean are excluded from the 100 km bandwidth, because borders in this area are likely to have been drawn with knowledge of local conditions.

On the other hand, if one looks in Figure 3 at the area near the Ghana-Togo border, there is somewhat more light on the Ghana (common law) side than on the Togo (civil law) side. If one looks at the borders between the Cote d'Ivoire, Guinea, Mali, and Burkina Faso, there is more light on the Cote d'Ivoire side, even though all four of these countries are former French colonies with civil law legal systems. These contrasts encapsulate the main points of this paper. There is no consistent advantage of common law over civil law, and there are considerable differences between countries that have nothing to do with their legal or colonial origins.

Figure 4 below shows a further close-up of one section of the border between Ghana and the Cote d'Ivoire.

Figure 4: Lights in One Section of the Ghana-Cote d'Ivoire Border, 1995

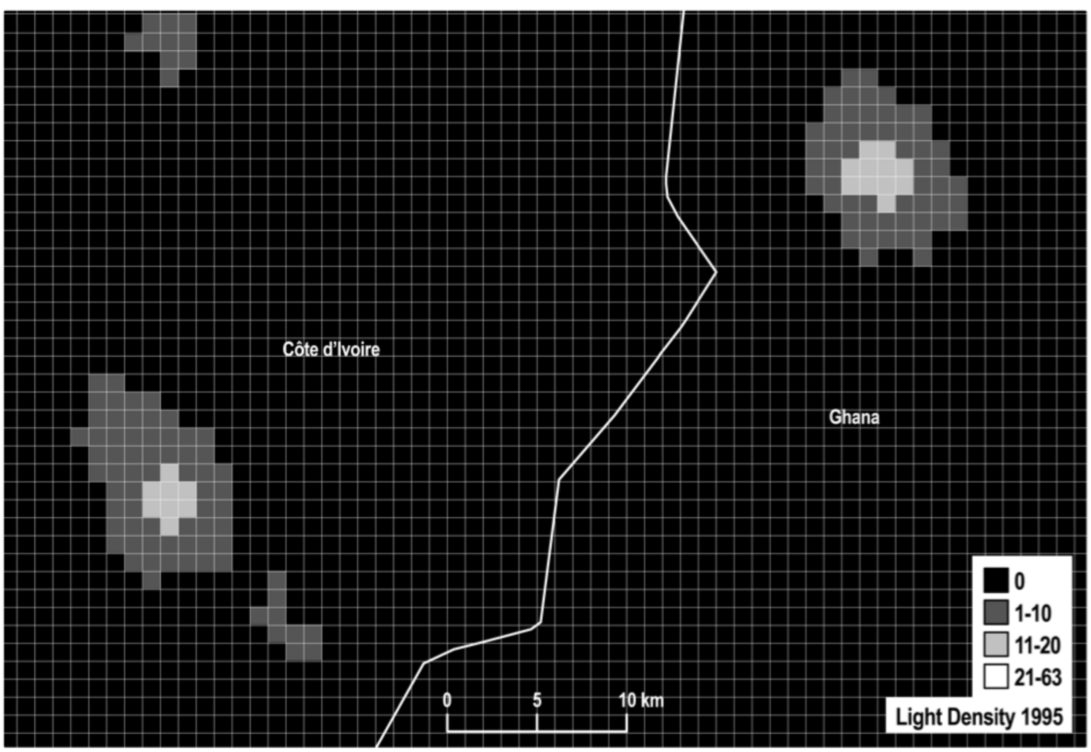


Figure 4 shows two medium-sized cities, Agnibilekrou in Cote d'Ivoire and Dormaa

Ahenkro in Ghana. Both had tens of thousands of inhabitants. Each square of the grid is roughly a square kilometer, the resolution of the light density data. Both cities had a small brightly light core of about ten square kilometers surrounded by about fifty square kilometers that are moderately lit. Areas outside the cities are almost completely dark.

Although 1992 was the first year that satellite data was made available to the public, we focus on data from 1995, an early year where we find the data to be more reliable, and from 2013, the most recent year the data is available. The luminosity variable reports a composite created by overlaying all images for the calendar year and dropping images where clouds, the aurora, solar glare, lightning or fires would have distorted the data (Michalopoulos and Papaioannou, 2013). It should be noted that there are a number of shortcomings of luminosity data. Chen and Nordhaus (2011) point out some of the problems with using nighttime light data, but nevertheless, they conclude that luminosity data have informational value, especially for regional analyses conducted in areas with poor data collection, which describes much of Africa.

Numerous studies have analyzed a variety of economic issues using nighttime lights, and several scholars have tested the accuracy of these data as a proxy for economic performance (Henderson, Storeygard and Weil, 2002; Chen and Nordhaus, 2011; Pinkovskiy and Sala-i Martin, 2016). The studies most similar to ours are Michalopoulos and Papaioannou (2013, 2014) and Pinkovskiy (2017). Michalopoulos and Papaioannou (2013, 2014) use nighttime light data and regression discontinuity analysis to examine the relationship between pre-colonial ethnic institutions and modern economic performance in Africa. In their 2014 article, they examine ethnic groups divided by national borders and investigate whether the quality of national institutions (principally rule of law and corruption) affect the amount of light across the national border. They find no effect. Although their approach is very similar to the one taken in this article, they do not study the effect of legal or colonial origin. In their 2013 article, Michalopoulos and Papaioannou find that the complexity of pre-colonial governments correlates highly with the amount of nighttime light and thus economic performance. Ethnicities that lacked "any form of centralized political organization," do worse today than those which were organized into "paramount chiefdoms," while those that were "part of large states" do best now (Michalopoulos and Papaioannou, 2013, pp.119,126-131). Pinkovskiy (2017) uses nighttime lights to document the importance of national borders and thus of national policies and institutions. For example, he examines the difference in growth rates between eastern European nations that joined the European Union in the early 2000s (such as Poland and Romania) and those that did not (such as Ukraine and Moldova). He finds that there are often discontinuities in growth rates as measured by changes in nighttime light across borders, including borders in Africa. He also finds that differences in growth rates are better predicted by measures of rule of law than by education, trust, or infrastructure quality. Pinkovskiy (2017) therefore shares two key features with the approach in this paper: regression discontinuity analysis at modern state borders and explanation of differences in terms of national institutions. Unlike our analysis, however, he does not analyze legal origin or other colonial institutions.

3.1.2 Survey Data

We rely on the Demographic and Health Surveys (DHS) performed by USAID for data on six outcomes: (1) the height in centimeters of women 15 to 49 years old, (2) whether the household has electricity, (3) the flooring material in the house, (4) the type of latrine or toilet facility in or used by the household; (5) whether at least one household member has a cellular telephone; and (6) whether the household has a means of non-human transport.[3] The DHS surveys provide nationally representative samples ranging in size from

[3]Electricity, flooring material, toilet facility, cellular phone, and transport data are from the DHS household level survey, while the height data comes from individual-level DHS survey data.

5,000 to 30,000 households and have been conducted roughly every five years since the 1980s. Interviewers trained by USAID visited households in person, interviewed respondents orally, and measured height and other physical variables directly. The intervals between surveys in sub-Saharan Africa vary dramatically; some countries have never been surveyed, and some countries were surveyed only in the 2010s. Most but not all data in the DHS are geolocated. Because of our regression discontinuity approach, we analyze only the geolocated data. In order to preserve anonymity and privacy, latitude and longitude coordinates are provided for the centroid of a geographic cluster of roughly 20 to 40 households.

Height data has been systematically collected by the DHS on women between 15 and 49 years old starting in 1992. Survey personnel (”enumerators”) were trained on height measurements according to World Health Organization (WHO) guidelines and used measuring boards with head pieces so they could record height to the nearest millimeter (Moradi, 2010).[4] The height data are subject to a number of potential selection and external validity issues. First, if mortality and height are related, there could be survivorship bias. Fortunately, this bias is likely to mean that our results underestimate the true difference between female height in common and civil law countries because, in general, shorter people are more likely to die earlier. This means that, if height is greater in one group than another when the both are young, as both groups age, the heights will converge, at least partially. So, to the extent that we measure the height of older persons, which is especially the case for our analysis of women born in the colonial period, the regression coefficients probably underestimate the extent to which women in civil law countries are taller. Two studies address survivorship bias in Africa, and both suggest it is a relatively minor issue (Alter, 2004; Moradi, 2009).

[4] Although DHS collects height measurements on male and female children, they have not systematically collected height data on men, so we analyze only female height. We dropped observations with heights under 90 and over 300 centimeters as they likely were the product of coding errors.

Second, DHS surveys have different and sometimes very large rates of missing observations for height. The missing observation rates range from 2.1 to 51.4 percent by country. Based on our understanding of the methodology the DHS followed, we have no reason to believe this bias is systematic or correlated with any variable of interest. We also have run alternative specifications for household electricity and found that including or omitting observations that are missing for height has no substantive impact on the results. This suggests that there are not meaningful differences between those whose height was measured and others.[5]

Third, because the survey only measures the height of women, one might wonder whether the results generalize to men. Although women are generally shorter than men, that difference might be even larger in an environment where gender discrimination resulted in women being disfavored in terms of nutritional health. Klasen (1996) describes Sub-Saharan Africa as a region where the nutritional status of women is relatively favorable in comparison to men, and Moradi (2009) found a high linear correlation between the heights of men and women in a cross-section of 89 African populations. So it seems likely that our analysis of female height would generalize to men.

We also analyze five key variables measured at the household level: electricity, flooring, sanitation (access to toilets or improved latrines), cell phone ownership, and ownership of non-human-powered transport.

Electricity is a key indicator of economic development and facilitates use of other consumer goods, such as a refrigerator or television. Survey data on whether a household has electricity also provides a nice cross-check on the nighttime lights. One would expect that areas with more electrified households would produce more nighttime light.

Flooring is another important indicator of development. In addition to being an im-

[5]Future iterations of the paper will examine the extent there are statistically and substantively meaningful differences for the groups for which the survey collected height data versus those for which data was not obtained.

portant indicator of comfortable living conditions and thus standard of living, improved flooring contributes to health as non-earth flooring is associated with diarrhea and malaria (Snyman et al., 2015; Koyuncu et al., 2020). The DHS survey instrument includes flooring codes for (1) earth or sand, (2) dung, (3) wood planks, (4) palm or bamboo, (5) parquet or polished wood, (6) vinyl or asphalt strips, (7) ceramic, marble, porcelain tiles, or terrazo, (8) cement, (9) woolen or synthetic carpet, or (10) other material. We do a dichotomous recoding of the variable where the variable is equal to 0 if the flooring primarily consists of earth, sand, or dung, and is equal to 1 if it is an improved material, such as wood or cement.[6]

Sanitation facilities are also important indicators of standard of living and contribute to health. One important indicator of sanitation is access to an improved latrine or toilet. The World Health Organization (WHO) defines an improved toilet as ”one that likely hygienically separates human excreta from human contact.” We follow their criteria by coding improved toilets according to standards established by WHO and the DHS. Specifically, the variable is equal to 1 if the toilet is a flush toilet, composting toilet, ventilated pit latrine, or pit latrine with a slab. Unimproved pit latrines or other less sanitary arrangements are coded as 0. This coding is also consistent with the Millennium Development Goals.

In addition to the health- and housing-related variables, we also analyze communication and transportation. Cell phones are not only a valued consumption good, but they also increase access to information related to markets, education, health, public safety, and government. Cell phone use in developing countries is associated with reduced gender inequality, higher contraception use, and lower maternal and child mortality. (Ro-

[6]We drop a small number of observations that are coded as ”other” material since including them is likely to increase measurement error. The DHS uses the same binary coding scheme in the utilization of flooring for its wealth index measure (Rutstein and Johnson, 2004). Specifically, in the country specific tables in the Rutstein and Johnson (2004, pp. 19-23) report, the flooring variable is coded as if the principal flooring is made of dirt, sand, or dung.

tondi et al., 2020). Our cell phone variable is equal to one if someone in the household has a mobile phone.[7]

Finally, we analyze whether or not the household possesses a means of non-human transportation. Transport provides increased access to markets where individuals – especially farmers and artisans – can sell products. It also means a wider range of employment opportunities (Centre, 2002). Because of the varied geographic heterogeneity across Sub-Saharan Africa, the variable is dichotomous and equal to one if the household has any means of non-human transport including a car, truck, motorcycle, motorboat, or animal-drawn cart.

We selected these outcomes *a priori*[8] primarily for two reasons. First, these indicators have been identified in the literature and by international organizations as important measures of economic well-being in developing countries. For example, the World Bank includes electricity access, height (stunted growth), and cell phone access as featured indicators among its World Development Indicators. The United Nations Millennium Development Goals (MDG) include cell phone and improved sanitation access as two of its 60 development indicators. The 2015 MDG report also mentions electricity access and durable housing (among other factors) as important for poverty alleviation, and stunted growth as an important indicator of child development. Electricity and flooring, in combination with the possession of other durable consumer goods, are also two inputs utilized to calculate a wealth index utilized by the DHS.[9]

Second, these measures lend themselves to principled measurement across Sub-Saharan Africa. The measures all have a clearly ranked ordering tied to economic well-being and

[7]The measure is admittedly a bit coarse since the DHS does not consistently provide information as to whether the cell phone is a smart phone or not.

[8]To be clear, we did not analyze any other variables in the DHS dataset. We selected these outcomes based on the reasons noted above before we did any analysis of the data.

[9]We do not use the DHS wealth index because it is normalized by country and therefore cannot be used for cross-border comparisons. In addition, analysis of individual variables usually provides more insight than an index.

are relevant to all parts of Africa. In contrast, other potential measures, such as wall or roofing material, reflect the local availability of certain natural materials and would be more difficult to rank.

3.1.3 Legal and Colonial Origin Data

This paper analyzes twenty-seven borders. These are all the borders between sub-Saharan African countries where one country has a legal system based on the common law, and the other has a legal system based on civil law.[10] A small number of borders was excluded because one or both of the relevant countries had legal origins or colonial history that would not fit into the categories used in our analysis.[11] Areas within 20 kilometers of the coast were also excluded, as borders in these regions were drawn with good knowledge of local conditions and therefore are not exogenous.

These borders share two important characteristics. First, the borders we examine were drawn mostly arbitrarily, in line with the empirical strategy that we propose. Second and relatedly, the borders show no obvious differences that privilege one side or the other with geographic endowments that would spur economic development. Covariate balance tests, described in greater depth in the next section, confirm that the areas on both sides of the border are similar in terms of key geographic variables.

Legal origin was initially coded by La Porta, Lopez-de Silanes and Shleifer (2008).

[10]Sub-Saharan countries are those which, at least in part, are south of the Sahara. Our analysis thus excludes countries that border the Mediterranean (such as Algeria and Egypt) and Western Sahara. These countries have a radically different history from the remainder of Africa – including incorporation into the Roman and Ottoman empires – making their exclusion appropriate. Our analysis includes countries such as Niger and Mauritania, even though most of their territory is in the Sahara, because they have some territory south of the Sahara and much of their population resides south of the Sahara. Countries with legal systems that are a hybrid of common law and civil law, such as South Africa and Zimbabwe, are analyzed only in Section 5.

[11]Borders involving Liberia, Eritrea, and Ethiopia were omitted because these countries were not colonized. Borders involving Namibia were omitted because it was ruled by South Africa from 1920 to 1970. Borders involving Cameroon were omitted because it was formed the merger of French and British colonies. Somalia was omitted because it was formed by the merger of Italian and British colonies. Djibouti was excluded, because its only borders are with countries that are excluded (Eritrea, Ethiopia, and Somalia)

That coding was extended and corrected by Klerman et al. (2011), who also coded for colonial origin, where colonial origin is the dominant colonial power in the period before independence. Table 1 shows the coding that we used to classify the legal and colonial origin of the 38 countries in our data set. Figure 5 maps the countries and borders. Our results focus on legal origin. Colonial origins are not used in our primary results, but are relevant to one of the robustness checks.

Table 2 categorizes the twenty-seven border pairs analyzed in this paper by the legal and colonial origin of each border pair. There are eleven common law/French civil law borders, eleven common law/non-French civil law borders, and five non-French civil law/French civil law borders.

3.1.4 Ethnicity Data

Our identification strategy relies partly on the anthropological work of George Murdock, who mapped ethnic groups in the last half of the nineteenth century (Murdock, 1959). This aspect of our identification strategy was also used by Michalopoulos and Papaioannou (2014) and Anderson (2018). Specifically, we focus on regions where national borders split an ethnic group. Thus, we can analyze the effect of different colonizers and their imposition of legal institutions on people with very similar cultural backgrounds.

Figure 6 shows the boundaries of ethnic groups as mapped by Murdock (1959), with national borders superimposed, and Figure 7 shows a close-up of West Africa, where the ethnicities are labeled and the way state borders divided ethnic groups is patent. In our primary specification, we analyze all areas where the same ethnic group was partitioned by a modern the border. In some cases, there are multiple ethnic groups split by the same contemporary border, which increases the external validity of our findings, since we are able to measure the impact of colonial and legal origin on economic development for multiple ethnic groups.

Table 1: Legal and Colonial Origin for Sample Countries

		Legal Origin	
		Common Law	Civil Law
Colonial Origin	Britain	Gambia (GMB) Ghana (GHA) Kenya (KEN) Malawi (MWI) Nigeria (NGA) Sierra Leone (SLE) South Sudan (SSD) Sudan (SDN) Tanzania (TZA) Uganda (UGA) Zambia (ZMB)	
	France		Benin (BEN) Burkina Faso (BFA) Central African Republic (CAF) Chad (TCD) Cote d'Ivoire (CIV) Gabon (GAB) Guinea (GIN) Mali (MLI) Mauritania (MRT) Niger (NER) R. of Congo (COG) Senegal (SEN) Chad (TCD) Togo (TGO) Benin (BEN)
	Belgium		Burundi (BDI) D. R. Congo (COD) Rwanda (RWA)
	Portugal		Angola (AGO) Guinea-Bissau (GNB) Mozambique (MZO)
	Spain		Equ. Guinea (GNQ)

Figure 5: Map of Legal and Colonial Origin

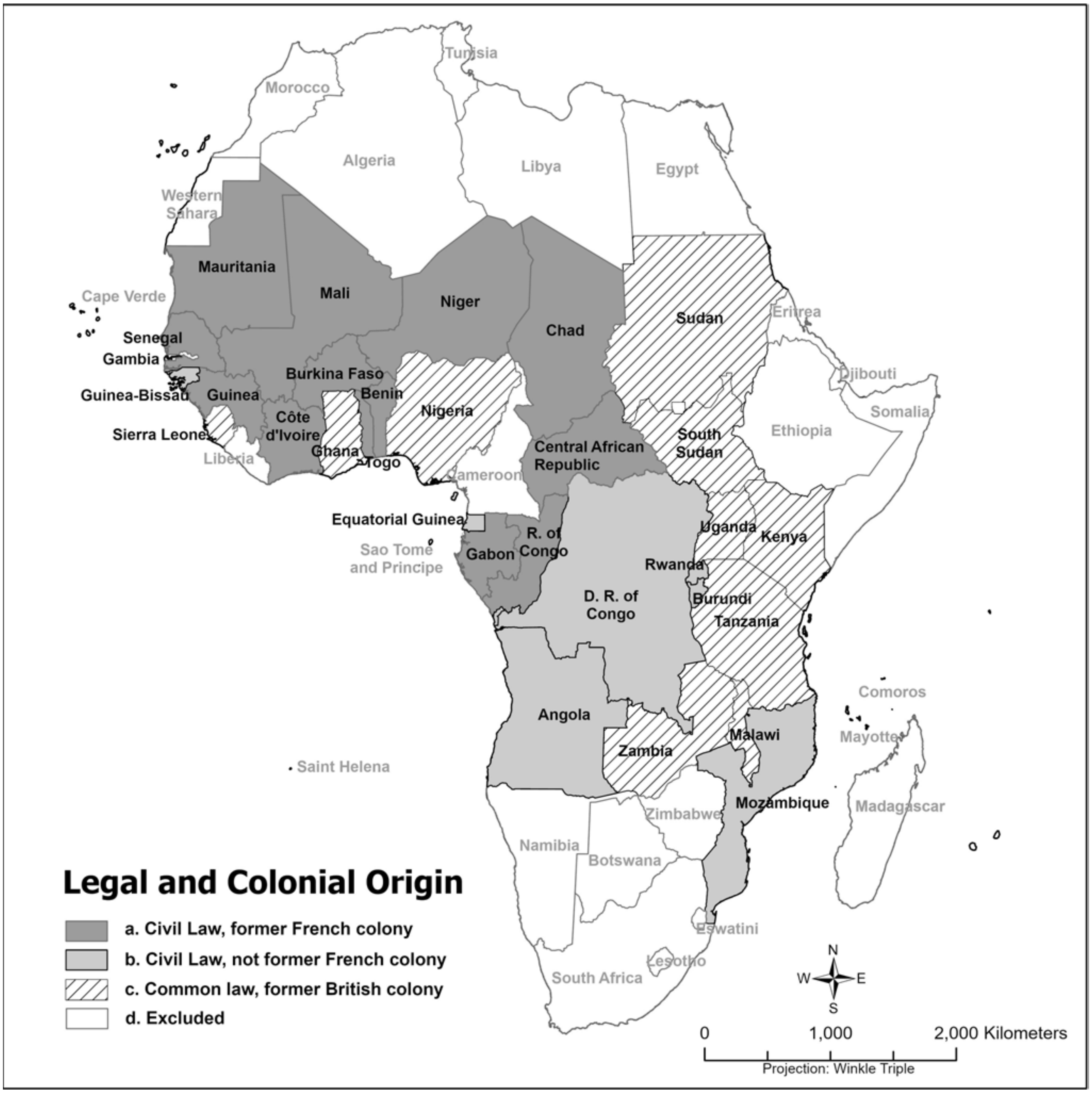


Figure 6: Ethnic and National Boundaries

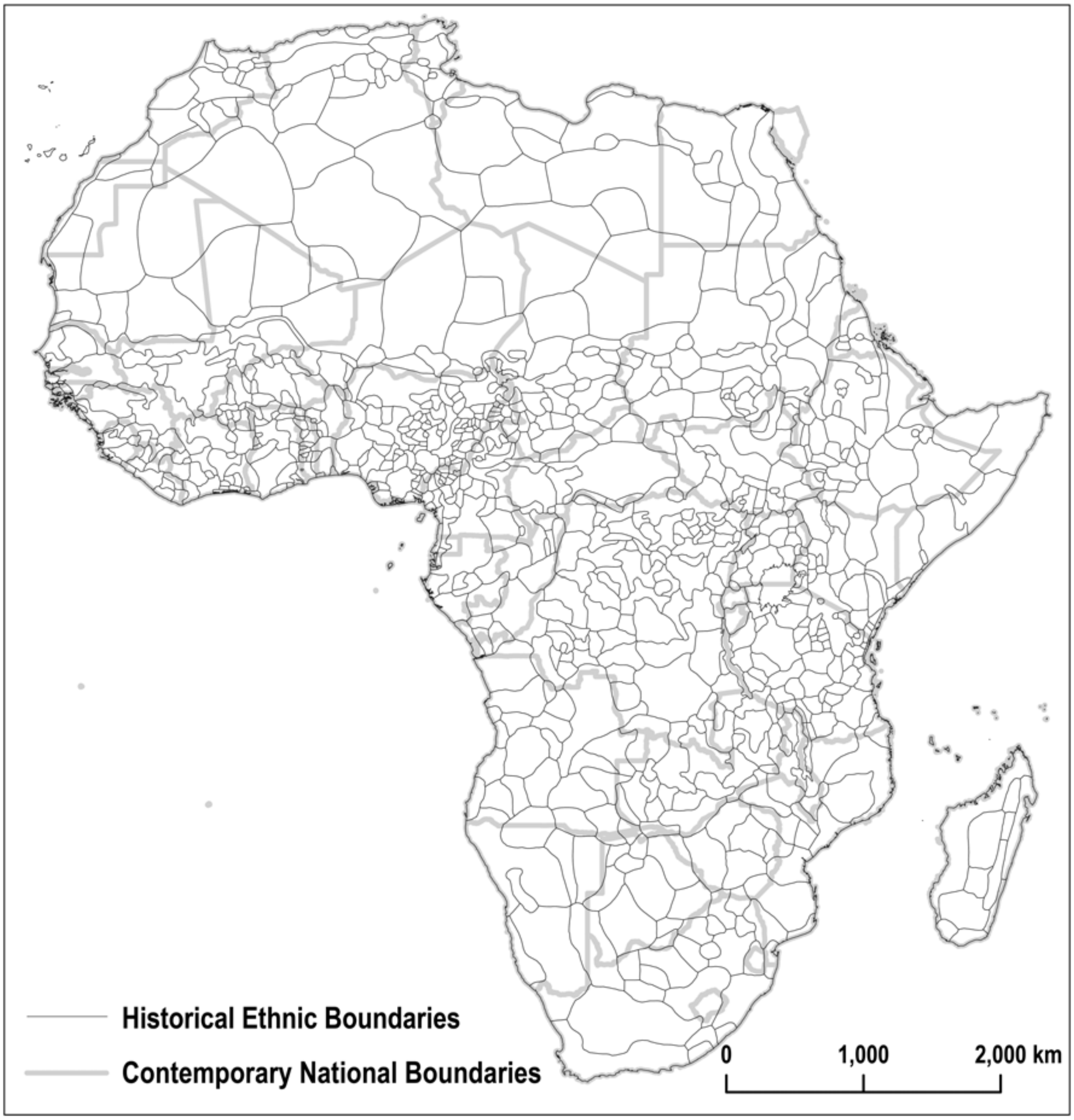
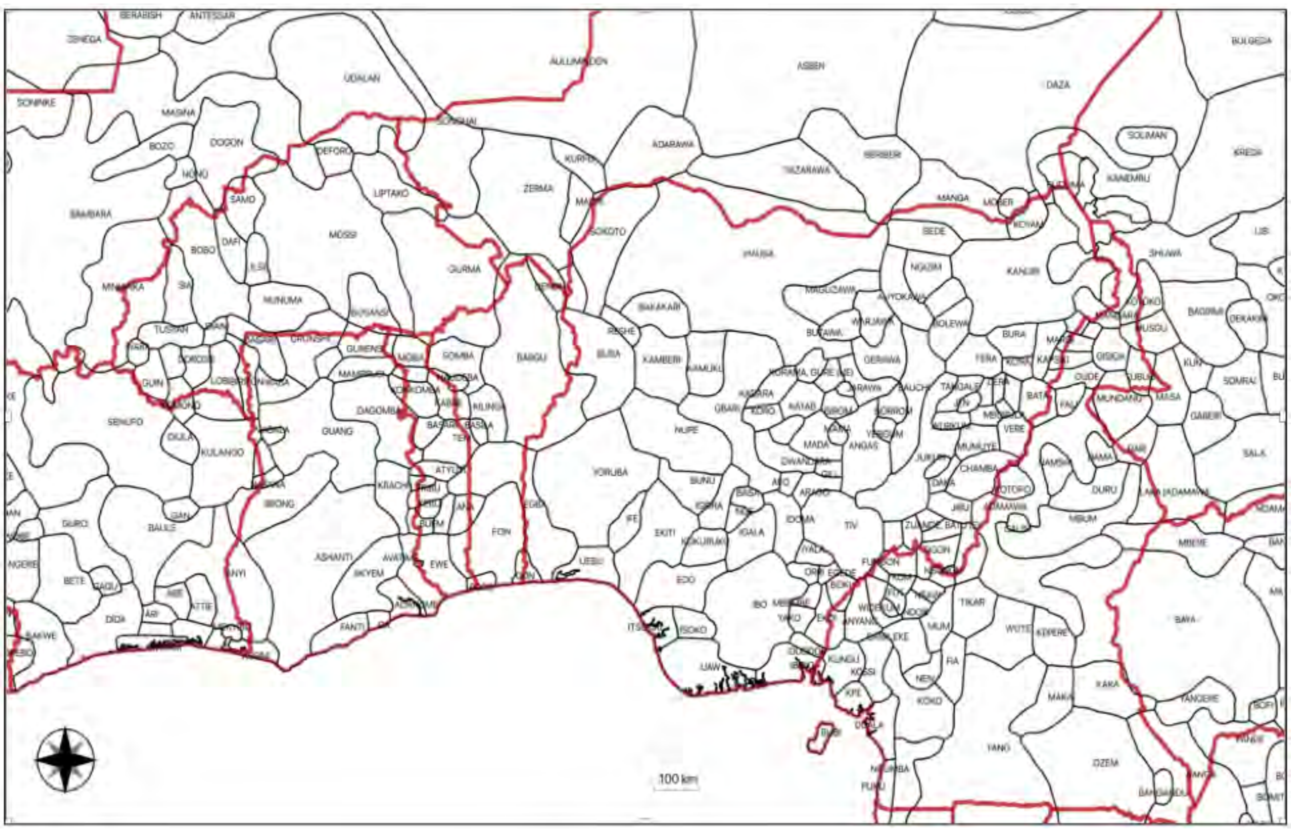


Table 2: Borders by Legal and Colonial Origin

Common Law and Civil Law, French	**Common Law and Civil Law, Not French**	**Civil Law, Not French and Civil Law, French**
Gambia-Senegal	Malawi-Mozambique	D.R. Congo-C.A.R.
Ghana-Burk. Faso	S. Sudan-D.R. Congo	D.R. Congo-Congo
Ghana-Cote d'Ivoire	Tanzania-Burundi	Eq. Guinea-Gabon
Ghana-Togo	Tanzania-D.R. Congo	Gin. Bissau-Guinea
Nigeria-Benin	Tanzania-Mozambique	Gin. Bissau-Senegal
Nigeria-Chad	Tanzania-Rwanda	
Nigeria-Niger	Uganda-D.R. Congo	
S. Sudan-C.A.R.	Uganda-Rwanda	
Senegal-Guinea	Zambia-Angola	
Sudan-C.A.R.	Zambia-D.R. Congo	
Sudan-Chad	Zambia-Mozambique	

Figure 7: Ethnic and National Boundaries, West Africa



3.1.5 Other Geographic Data

Our models incorporate raster datasets derived from both remote sensing and interpolation. Raster data are grids stored in a computer, corresponding to pixels that hold value (DeMers 2002; Tomlin 1990). Data such as nighttime lights, elevation, and terrain ruggedness are composites or derivatives of remotely sensed images (Jensen 2007; 2016). In contrast, temperature, precipitation, and population data are interpolated from point-based observations or counts by unit (Jensen 2007; 2016). For geospatial analysis and modeling, conversions are often made between vector and raster data to combine appropriately, with vector data interpolating to a gridded raster surface and raster cells corresponding to grids of points calculated from their centroids (source? Need to hunt this down).

Elevation impacts how humans settle and move, and thus, it was included as a variable in the analysis through the use of digital elevation models, or DEMs. A DEM is a raster file in which a grid of regularly spaced points corresponding with pixels represents a continuous elevation value for the covered area (DeMers 2002; Tomlin 1990). While there are many options for DEMs, this research used GMTED 2010 at 30-arc-second resolution (Danielson and Gesch, 2011) as the reference dataset used to construct a grid of cells for the African continent. Subsets of this data were used to extract other raster values and as origins for distance variables.

Terrain ruggedness refers to the level of change in elevation over a landscape or the topographic heterogeneity (Esri Analytics Team. 2020; Riley et al. 1999). Elevation change can profoundly affect human development and the cost of traveling between places (Tobler 1993). We quantified this ruggedness with the topographic ruggedness index (TRI), which measures local topographic relief derived from the DEM by comparing elevation differences between a grid cell and its eight neighbors (Riley et al. 1999).

WorldClim2 precipitation and temperature datasets (Fick and Hijmans, 2017) are 30-year annual averages created using thin-plate splines and covariates to interpolate raster surfaces from weather station observations.

GHS-POP population distribution and density data (European, 2015) approximate the number of people per grid cell; for these, GPWv4 residential population estimates (CIESIN; Center for Informational Earth Science Information Network) were disaggregated from census or administrative units and allocated to pixels, informed by the distribution and density of built-up areas as mapped in the Global Human Settlement Layer for the corresponding time frame (Center for Informational Earth Science Information Network, 2018).

For geospatial analysis and modeling, conversions are often made between vector and raster data to combine them appropriately, with vector data interpolated to a gridded raster surface. Our models incorporate raster datasets which originated as both pixel-based and non-pixel-based data: nighttime lights, elevation, and terrain ruggedness are composites or derivatives of remotely-sensed data. Temperature, precipitation, and population data are interpolated from point-based observations or counts by unit.

3.1.6 Summary Statistics

Table 3 below provides summary statistics for all variables used in this paper.

3.2 Empirical Strategy and Inference Validity

In the natural experiment we are exploiting, the reliability of causal inference rests on the assumption of "as-if" random assignment of the treatment at the border (Dunning, 2008; Keele and Titiunik, 2015; Mattingly, 2017). For our study, this would involve an actor drawing borders arbitrarily so that those living close to the border on one side were similar to those on the other side of the border, except for the treatment. We employ three important strategies to ensure the presence of this "as-if" random assignment. First,

Table 3: Summary Statistics

Variable	Obs.	Mean	Std. Dev.	Min	p25	Median	p75	Max
Nighttime Satellite Data								
Ln(Light Density 1995 + 0.01)	1,384,040	-4.548	0.610	-4.605	-4.605	-4.605	-4.605	4.143
Population 1995	1,384,040	28.635	486.373	0.000	0.000	0.000	0.000	114,974.100
Population 2000	1,384,040	37.104	549.787	0.000	0.000	0.000	0.000	116,959.800
(Ln(Light Density 1995 + 0.01))/Population	159,906	-7.357	2.503	-16.258	-9.121	-7.722	-5.759	7.860
Elevation (m)	1,384,040	735.026	438.938	0.000	339.000	700.000	1,076.000	4,685.000
Ruggedness	1,384,040	17.206	25.737	0.000	5.601	9.937	16.860	513.167
Average Annual Temperature (°C)	1,384,040	24.072	3.028	1.238	21.496	24.721	26.567	29.196
Average Annual Precipitation (mm)	1,384,040	1,014.435	452.356	14.000	784.000	1,063.000	1,232.000	3,384.000
Soil Suitability	1,383,491	0.418	0.232	0.003	0.280	0.423	0.578	0.988
Malaria Ecology Index	1,384,040	13.230	8.465	0.000	5.539	13.133	19.624	33.396
Distance to the Capital	1,384,040	749,355	501,475	0.000	336,297	619,034	1,106,460	1,940,926
DHS Survey Household and Individual Data								
Electricity	148,180	0.164	0.370	0	0	0	0	1
Height (Pre-Independence)	722	159.808	6.228	128.500	155.800	159.700	163.600	190.000
Height (Full Sample)	75,786	158.802	7.017	90.000	154.500	158.800	163.200	207.000
Floor	147,966	0.353	0.478	0	0	0	1	1
Sanitation	147,775	0.476	0.499	0	0	0	1	1
Cell Phone	117,394	0.550	0.497	0	0	1	1	1
Transport	148,711	0.420	0.494	0	0	0	1	1

Notes. All nighttime satellite statistics are for areas within 50 km of the Civil Law-Common Law borders analyzed. DHS household data is for all survey variables, except height, which is for individual women 15 to 49 years old. All survey dated in this table is unweighted.

where possible, we examine historical sources to substantiate the random drawing of the border (Ajala, 1983; Brownlie, 1979; Touval, 1966). Second, we conduct covariate balance checks to see if geographic variables show statistically and substantively distinguishable differences. Third, we exclude areas closer to the ocean, because these borders were more likely to be drawn with knowledge of local characteristics. These three strategies help ensure that the location of borders was not influenced by circumstances that affect economic development, which is, of course, essential to the validity of our identification strategy. (Angrist and Pischke, 2008; Michalopoulos and Papaioannou, 2014).

3.2.1 History

As previously mentioned, the extant historical literature shows that the colonizers drew African borders in an arbitrary or "quasi-random" manner. Asiwaju (1984), Wesseling (1996), Herbst (2000), and Engelbart (2009) provide reviews of this literature, while Michalopoulos and Papaioannou (2014) discuss the implications for geographic regression discontinuity analysis. Settlers and colonizers created "spheres of influence" on the continent without the intention of creating colonies. When they later expanded these spheres of interest into colonies, they did so without much information about the characteristics of the territories they were dividing. The main exception was areas close to the coast, where the colonizing powers knew the terrain well. The situation is admirably described by Lord Salisbury, British Prime Minister at the time of the partition of West Africa:

> We have been engaged in drawing lines upon maps where no white man's foot ever trod; we have been giving away mountains and rivers and lakes to each other, only hindered by the small impediment that we never knew exactly where the mountains and rivers were.[12]

[12] Lord Salisbury, cited in Asiwaju (1984, pp. 18-19).

3.2.2 Covariate Balance

The idea that borders were drawn ”as if” randomly is borne out in statistical tests to determine whether covariates exhibit ”smoothness” across the boarder. Table 4 shows the covariate balance for seven covariates for the twenty-two borders in our study at the 100 kilometers bandwidth standard in the literature. (Michalopoulos and Papaioannou, 2013) These seven covariates – elevation, ruggedness,[13] average precipitation, average temperature, soil suitability, and the malaria ecology index – ensure that neither side of the border had particular geographic advantages that would assist with their economic development. In Table 4, for each covariate, we estimate a local linear and local quadratic model where the covariate is the outcome, the key variable to be estimated is a treatment indicator coded for legal origin, with fixed effects for partitioned ethnic groups and clustering at the country level.[14] The models follow the same form as is described in the next section, which describes the estimation procedure in greater detail.

For the most part, there are no significant differences in the covariates across borders. For only one variable – Ruggedness – are the wild bootstrapped p-values under or close to 0.05. In addition, the robust CCT p-values are under 0.05 only for Distance to Capital (both local linear and local quadratic) and for Ruggedness (local linear only). Nevertheless, although the differences may be statistically significant, they are not substantively significant. The difference in ruggedness is less than 4.7 meters, which is less than a fifth of the standard deviation. Ruggedness measures changes in elevation within a kilometer; a change in elevation of just a few meters over a distance of one kilometer makes no difference for agriculture or any other purpose. Similarly, a difference of about 300 meters

[13]The topographic ruggedness index as proposed by Riley, DeGloria and Elliot (1999) is a measure of elevation change between the center cell in a three-by-three cell moving window and the eight cells immediately surrounding it. Nunn and Puga (2012) argue that ruggedness impeded the slave trade and led to favorable long-term outcomes. In this paper, the units of ruggedness are meters. In Nunn and Puga (2012), the units are 100 meters.

[14]We choose to cluster exclusively on country in light of recent work by Abadie, Athey, Imbens, and Wooldridge (2023).

Table 4: Covariate Balance

Covariates	(1) Elevation	(2) Ruggedness	(3) Avg. Temp	(4) Avg. Precip.	(5) Soil Suitability	(6) Malaria Ecology Index	(7) Distance to Capital
Local Linear							
Estimate	11.653	3.942	-0.095	1.775	-0.002	-0.155	320.000
Robust CCT							
95% CI	-55.532, 84.778	0.310, 9.048	-0.520, 0.331	-20.465, 26.950	-0.020, 0.018	-0.865, 0.280	-543.705, -58.032
p	0.683	0.036**	0.663	0.789	0.921	0.317	0.015**
Wild Bootstrap:							
95% CI	-39.410, 77.240	0.036, 9.037	-0.520, 0.308	20.110, 23.280	-0.029, 0.028	-0.902, 0.554	-776.243, 57.549
p	0.644	0.045**	0.774	0.874	0.855	0.626	0.133
Local Quadratic							
Estimate	14.492	4.682	-0.094	3.185	-0.001	-0.292	300.000
Robust CCT							
95% CI	-68.665, 64.171	-1.334, 5.053	-0.411, 0.393	-19.537, 26.659	-0.013, 0.025	-0.890, 0.124	-556.915, -55.868
p	0.947	0.254	0.965	0.763	0.534	0.139	0.017**
Wild Bootstrap:							
95% CI	-60.020, 104.500	-0.098, 10.280	-0.699, 0.386	-19.500, 29.060	0.027, 0.0288	-0.948, 0.278	-767.323, 77.436
p	0.713	0.056*	0.705	0.774	0.935	0.269	0.158
Observations	1,145,701	1,145,701	1,145,701	1,145,701	1,145,227	1,145,701	1,145,701

Note: $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.10$. Estimates follow the form of Equation 1 below, where each covariate is an outcome. All specifications rely on a 100 kilometer bandwidth and uniform kernel. We rely on robust confidence intervals and p-values developed by Calonico, Cattaneo, and Titiunik (CCT) (2014) and Calonico et al. (2019) in the first three rows of each panel. Confidence intervals and p-values utilizing a wild bootstrap are in the lower two rows of each panel. Standard errors are clustered at the country level.

in distance to the capital (less than a fifth of a mile) has no economic import, especially when one considers that the average distance to the capital is 749 *kilo*meters. Other differences are neither statistically nor economically significant. For example, the coefficient on average temperature indicates less than a 0.1 degree Celcius difference between civil and common law countries. This, of course, makes a lot of sense, as temperature and most other geographic variables seldom change dramatically over a small distance.

Covariate balance can also be seen more informally with satellite imagery. Consider Figure 8 below, which shows much of Western Africa. It is apparent that Niger (a French colony) is largely desert (tan), while Nigeria (a former British colony) has a mostly tropical savanna climate (much greener). Nevertheless, if one focuses on the areas close to the border between Nigeria and Niger, for example the 100km bandwidth indicated by the dotted lines, they are similar.

Figure 8: Satellite Image of Western Africa, 2019

Source: Google Maps

3.2.3 Estimation

We rely on a geographic regression discontinuity approach that estimates the effect of legal and colonial origin on outcomes reflective of economic well-being. Specifically, we estimate the following equation using both local linear and local polynomial regression:

$$y_i = \alpha + \beta T_i + f(\delta_i) + \eta X' + \gamma_i + \epsilon. \tag{1}$$

The dependent variable, y_i, reflects the level of economic well-being in the geographic area as measured by amount of logged light at night, logged per capita light at night, the height of 15 to 49 year old women in the household, or a binary variable indicating whether a household has electricity, an improved floor, a toilet or an improved latrine, at least one cellular phone, or non-human-powered transport.

T_i is a treatment indicator coded by the legal origin of the country which is equal to 1 if the country has common law and 0 if it is civil law. δ_i is the distance to the border, and X' is a matrix of control variables that includes a rich set of key covariates such as elevation, ruggedness, average temperature, average precipitation, and distance to the capital.[15] The distance to the capital is a proxy for central government control, as much of the literature shows that, all else equal, law enforcement and policy implementation more generally declines as distance from the capital increases (Michalopoulos and Papaioannou, 2014, pp. 190-196). $f(\delta_i)$ is either a flexible local polynomial or local linear function interacted with T_i allowing for different parameters on either side of the border. For example, for a linear specification, the $f(\delta_i) = \beta_1\delta_i + \beta_2\delta_i T_i$. Depending on the specification, we also include border pair, ethnic group, and interviewer year fixed effects, captured by the term γ_i for specifications that rely on survey data. For specifications where height is the outcome, we also include birth year fixed effects.[16] β is the RD quantity of interest, which gives the local average treatment effect (LATE) that we are seeking to estimate.

We cluster on the country. This approach is used in order to mitigate the concern of spatial autocorrelation and to account for arbitrary forms of heteroskedasticity, and has been incorporated in similar designs by Nunn and Wantchekon (2011) and Michalopoulos and Papaioannou (2013, 2014), and because it is at the level at which treatment is

[15]Our core specification lacks covariates, but we include covariates a robustness check in Section 5.

[16]We drop ethnic group fixed effects for specifications that are for the entire borders, which are included in the robustness checks.

being assigned. To improve the precision of our estimates, we include specifications with covariates.[17] We report point estimates for a symmetric bandwidth of 100 kilometers utilizing a uniform kernel. We show the robustness of the results by examining alternative bandwidths. We follow a recent literature that recommends using robust p-values and confidence intervals developed by Calonico, Cattaneo, and Titiunik (CCT) (2014) and Calonico et al. (2019). Because nearly all specifications have fewer than 20 clusters, we also report wild bootstrapped confidence intervals and p-values. Because of the small number of clusters, we think the wild bootstrap is more appropriate.[18]

4 Results

We start with a summary of regression results of the eight dependent variables of interest: light, light per capita, electricity, height, sanitation, flooring, cell phone, and transport. We then explore height in more detail because it can provide a unique window into pre-independence conditions.

4.1 Main Results

Table 5 below shows results for all eight dependent variables of interest in our preferred specification. All regressions are for partitioned ethnicities that straddle borders between common law and civil law countries because these specifications are the most reliable from a causal inference perspective. The independent variable of interest is a common law dummy variable; the omitted category is civil law, so coefficients reflect differences from that base category. A positive coefficient on common law therefore indicates better

[17] Covariates used in this version are average elevation, average annual precipitation, average annual temperature, distance to capital, and terrain ruggedness (Riley, DeGloria and Elliot, 1999; Nunn and Puga, 2012).

[18] Future iterations of the paper will also include results showing kernel robustness.

outcomes in terms of economic well-being in common law countries. In these regressions, we pool civil law countries for which France was the colonizer and civil law countries colonized by Belgium, Portugal and Spain because, as discussed in the next section, we do not find significant differences between civil countries based on their colonial origin. We have fixed effects for each ethnicity and, for survey variables, for year of survey observation. The height specifications also include birth year fixed effects. Because our covariate balance is good, we do not include covariates (although, as shown in Section 5, regressions with covariates are not significantly different).Observations involving survey data (Models 3-7) are weighted by the product of two weights: (1) a weight that DHS created to adjust for over- and under-sampling within countries, and (2) a weight we created to adjust for differences in sampling between countries. That second weight is one divided by the number of observations per country used in the relevant analysis (e.g. the number of observations per country for the relevant variable within 50 kilometers of studied borders and within a partitioned ethnicity).

The upper panel of the table shows the results of a local linear model, while the lower panel relates to a quadratic specification. We calculate confidence intervals and p-values in two ways: using a robust estimation approach developed by Calonico, Cattaneo, and Titiunik (2014) and Cattaneo et al. (2019), and employing a wild bootstrap. As discussed in the methods section, we place greater emphasis on the wild bootstrapped results.

The general conclusion from the regressions is that there is no significant, consistent common law advantage. The coefficients are of mixed signs. Five of the eight coefficients in the local linear model are negative, indicating a civil law advantage. Five of the eight coefficients in the quadratic specification are also negative. Overall, the preponderance of negative coefficients is inconsistent with the idea that the common law produces consistently better outcomes.

Only one of wild bootstrap p-values – Transport in the quadratic specification – is

Table 5: Summary of Main Results

Outcome	Model 1 Light	Model 2 Light per Capita	Model 3 Electricity	Model 4 Height	Model 5 Floor	Model 6 Sanitation	Model 7 Cell Phone	Model 8 Transport
Local Linear								
Estimate	0.012	-1.026	-0.028	-0.053	-0.008	0.023	0.015	-0.072
Robust CCT								
95% CI	0.000, 0.042	-1.202, 0.239	-0.080, 0.046	-0.959, 0.105	-0.098, 0.070	-0.068, 0.146	0.16, 0.141	-0.128, -0.046
p	0.045**	0.003***	0.589	0.115	0.743	0.476	0.014**	0.000***
Wild Bootstrap:								
95% CI	-0.028, 0.050	-2.088, -0.596	-0.069, 0.051	-1.121, 0.831	-0.146, 0.085	-0.213, 0.170	-0.084, 0.095	-0.126, 0.031
p	0.479	0.341	0.656	0.713	0.644	0.816	0.694	0.220
Local Quadratic								
Estimate	0.021	-0.712***	-0.019	-0.465	-0.021	0.040	0.088**	-0.091
Robust CCT								
95% CI	-0.022, 0.066	-1.418, -0.553	-0.091, 0.049	-0.636, 0.9211	-0.074, 0.103	-0.061, 0.128	-0.020, 0.165	-0.093, 0.022
p	0.331	0.000***	0.556	0.720	0.749	0.488	0.012**	0.225
Wild Bootstrap:								
95% CI	-0.004, 0.052	-1.582, 0.508	-0.101, 0.094	-1.579, 0.540	-0.165, 0.070	-0.212, 0.210	-0.070, 0.267	-0.164, 0.000
p	0.111	0.332	0.969	0.307	0.552	0.981	0.272	0.049**
Observations	1,145,701	147,483	135,794	30,548	135,682	135,478	87,000	136,320

Note: $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.10$. Estimates follow the form of Equation 1. All specifications rely on a 100 kilometer bandwidth and uniform kernel. Cattaneo, Calonico & Titiunik robust confidence intervals, and *p*-values are utilized in the first three rows of each panel. Confidence intervals and *p*-values utilizing a wild bootstrap are in the lower two rows of each panel. Standard errors are clustered at the country level. The treatment indicator, T_i, is equal to 1 for the common law side of the border.

significant at the conventional five percent level, and it shows a *civil* law advantage.

Four variables have robust *p*-values that, in at least one specification, are less than 0.05: Light (linear only), Light per Capita, Cell Phone, and Transport (linear only). Of these, the estimates for two of the outcomes are negative, which means there is roughly equal evidence in favor of common and civil law, but certainly no strong evidence for a common law advantage.

Of course, the confidence intervals, especially with the wild bootstrap, usually include zero, so we cannot exclude the possibility of a common law advantage for most outcomes. For example, the wild bootstrap 95 percent confidence intervals for Sanitation suggest that there might be about twenty percentage points more improved latrines or toilets in common law countries, which would be a major common law advantage in sanitation.

Nevertheless, the point estimates and p-values provide no support for the idea that the common law produces consistently superior economic outcomes.

The conclusions from the regression table are confirmed by graphical analysis. The graphs in Figure 9 show a second order polynomial. The running variable (horizontal axis) is distance to the border. The vertical dotted line shows the border itself. Civil law (control) is to the left and common law (treatment) is to the right . The only graph showing a noticeable break at the border is Light per Capita, and it suggests economic conditions are *worse* on the common law side. Light, Sanitation, Cell Phone, and Transport show small breaks at the border, although the direction of the difference varies. Overall the graphs, like Table 5 suggest no overall advantage to the common law.

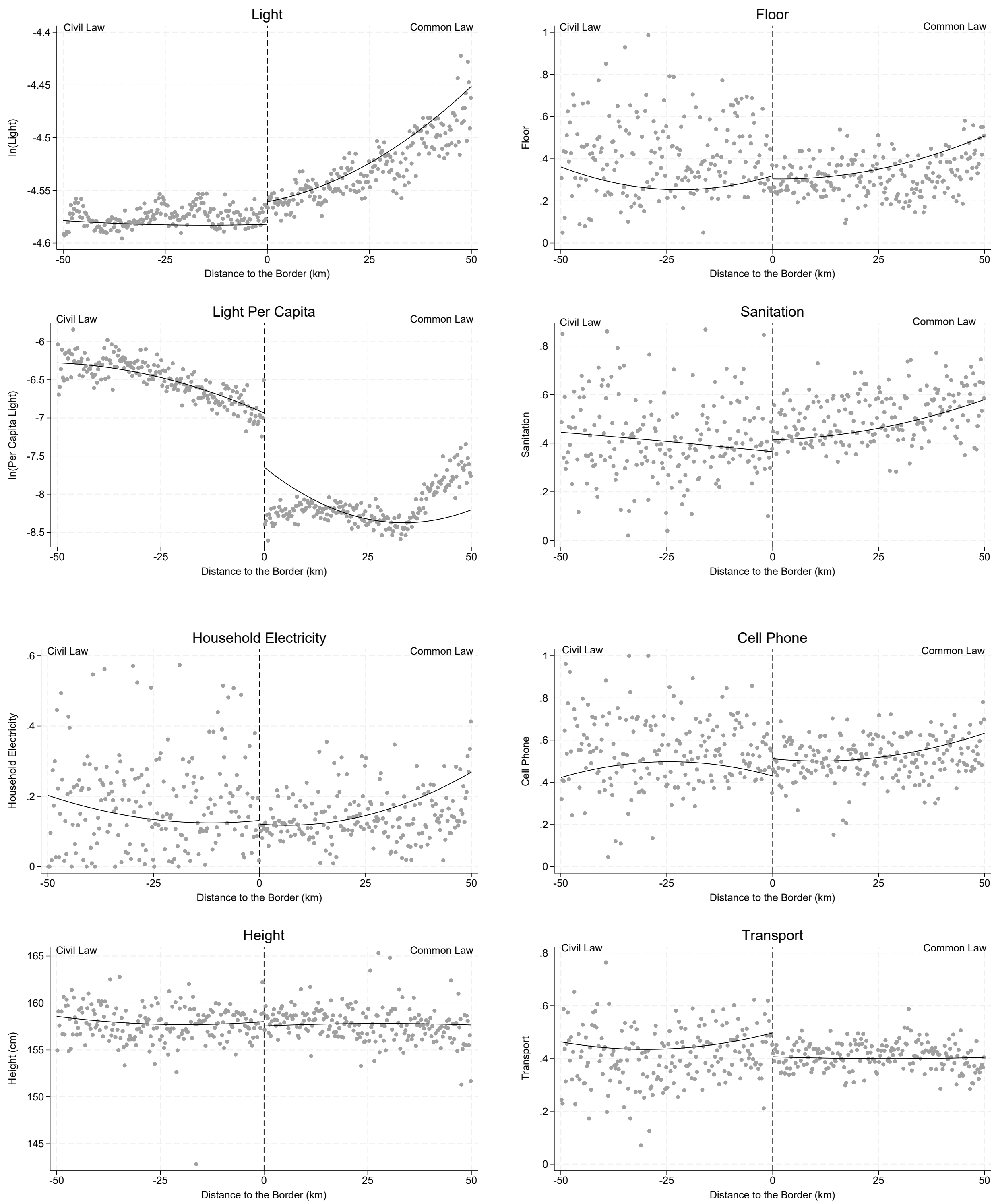
4.2 Colonial Height

Results relating to height (Table 5, Model 4) are particularly notable. Height is a good indicator of nutrition and thus provides a reliable window into economic conditions, especially for poor countries where many do not have sufficient income to buy food of adequate quality or quantity, and malnutrition is a significant problem. Foods that are high in protein, such as meat, are important for height, but are also more expensive. Height data in the DHS survey are available on a consistent basis only for women. Women's height is a marker not only of economic conditions, but also of gender equality, intra-household power, and discrimination.

Results in Table 5 for female height included all birth cohorts combined. The sign of the common law coefficient negative in both the linear and quadratic specifications. Only the *p*-value for the local linear estimate was close to statistical significance at conventional levels, and only for the robust *p*-value (not for the wild bootstrap). The height analysis is therefore inconclusive, providing only weak evidence of a civil law advantage.

One of the reasons height is such a powerful outcome variable is that, like tree rings,

Figure 9: Graphical Regression Discontinuity Results



Note: Data is fit to a local quadratic polynomial using the same form of Equation 1.

observations in a later year can be used to measure conditions in prior years. Because adult height is largely determined by the nutrition of the mother during pregnancy and by the nutrition of the baby during the first two years of life, height measured in the 1990s and 2000s can provide information about nutrition, and thus economic and social conditions, in pre-independence Africa, if the woman whose height is measured was born before independence. To focus on colonial conditions, Table 6 examines the adult height of persons born two or more years before independence. Such persons were in utero and had their first two years of infant growth during the colonial period, so their adult height is a good indication of colonial economic welfare. Unfortunately, relatively little data on the height of women born in the pre-independence period are available, so Table 6 analyzes only West Africa, where the borders are between former French and former British colonies. They became independent between 1957 (Ghana) and 1961 (Sierra Leone). The regressions thus analyze, for example, persons born in Ghana in or before 1955 and persons born in Sierra Leone in or before 1959. The precise dates for other countries vary depending on the year of their independence, but, with minor variations from place to place, the regressions primarily look at the height of adults born in the 1950s, because relatively few people in the dataset (0.53 percent) were born before 1950.

Models 2 and 3 in Table 6 are similar to the Model 4 (Height) and other regressions in Table 5, except only the height of women born before independence is analyzed. In addition, these regressions use DHS sample weights but do not use the weights related to the inverse of the number observations because some of the borders had so few observations that weighting in that way would have given undue weight to a small number of observations.[19] Standard errors are clustered by country.

The common law coefficients in Model 2 and 3 are mixed. The local linear coefficient is negative and small, while the local quadratic is positive and large. The *p*-values, of

[19]Results with weights related to the inverse of the number of observations are similar.

Table 6: Colonial Height Results

	Model 1 Difference in Means	Model 2 Local Linear	Model 3 Local Quadratic
Estimate	-1.452	-0.385	2.157
Robust CCT			
95% CI	-2.825, 1.544	-3.086, 5.935	-4.710, 8.591
p	0.565	0.536	0.567
Wild Btstrp.			
95% CI		-16.100, 15.090	-37.410, 30.280
p		0.859	0.547
Observations	722	722	722

Note: Estimates follow the form of Equation 1. All specifications rely on a 100 kilometer bandwidth and uniform kernel. The treatment indicator, T_i, is equal to 1 for the common law side of the border.

course, are also large, which means that the results should be treated with caution. The p-values are large primarily because the numbers of observations (722) is small.

The small number of observations suggests that it might be better to analyze the difference in means (e.g. polynomial of order zero) rather using than local linear or quadratic specifications (polynomials of orders one or two). Model 1 provides the difference in means. The coefficient is negative and large, suggesting that women in civil law countries were about one and a half centimeters taller, which is a big difference. The robust *p*-value, however, is very large. [20]

The fact that the results are so sensitive to specification, of course, means that one can draw now firm conclusion about height, and thus nutrition and economic conditions in pre-independence Africa.

[20] Interestingly, the bias-corrected *p*-value is very low (0.000), which suggests that perhaps the negative coefficient reflects real differences.

5 Robustness Checks

We performed numerous checks to confirm that results observed in the preferred specifications (Table 5) are robust to alternative specifications. In particular, we checked to make sure (a) that in alternative specifications the number of positive and negative coefficients remained roughly equal, indicating no consistent common law (or civil law) advantage, and (b) to the extent that there were results with low p-values, those were roughly evenly split between positive and negative coefficients, again to confirm the absence of a consistent advantage for common or civil law. While coefficients and p-values change a bit in the robustness checks, as in the preferred specification, neither common law nor civil law perform consistently better.

Tables 7 and 8 report the results of our robustness checks. The first panel in each table reproduces the preferred specification for comparison. Each robustness check makes a single change from the base specification. For the most part, the robustness checks produce similar results to the main specification.

As discussed above, in the preferred, core specification, ten of the sixteen coefficients are negative (indicating a slight civil law advantage), and, of the six variables with p-values less than 0.05, three are positive and three are negative, (indicating an advantage for neither legal origin).

The first robustness check adds the five covariates discussed above that are often used in this literature: elevation, ruggedness, average temperature, average precipitation, and distance to the capital. Our base specification does not include any covariates because, as discussed above, our covariate balance is very good. Panel (b) shows that adding covariates makes relatively little difference. The sign of ten of the sixteen coefficients remains negative, although a few coefficients flip signs. The p-values on many variables have gone up considerably so that only Transport remains with p-values that are statistically significant at conventional levels ($p < 0.05$). As in the core specification, the coefficient is negative, indicating better transportation in civil law countries.

The second robustness check, Panel (c), restricts analysis to borders between common law countries and civil law countries colonized by France. That is, it excludes civil law countries colonized by Belgium, Portugal, or Spain. It thus focuses on the difference between British and French colonialism and thus on West Africa, where French and British colonies border each other. By focusing on West Africa and just former French and British colonies, these regressions remove any possibly confounding regional effects or problems created by grouping former Belgian, Portuguese, and Spanish colonies. Results remain very similar to the preferred specification. Ten of the eighteen coefficients remain negative. Interestingly, the only coefficients that achieve statistical significance at conventional levels (i.e. $p < 0.05$) are negative. Notably, the coefficients for Height in both the local linear and local quadratic specifications are negative with p-values less than 0.05 in the wild bootstrap, indicating that those on the civil law side of the border are taller on average.

Robustness checks (d), and (e) perform bandwidth sensitivity checks. Panel (d) narrows the bandwidth from 100 kilometers to 50 kilometers, while (e) widens the bandwidth to 200 kilometers. The quadratic specification would not run properly with the 200 kilometer bandwidth, so no results are reported for that specification. The results change a bit. For the narrower bandwidth, only seven of the sixteen coefficients are negative, although the two of the three variables with p-values less than 0.05 are negative. So the results still indicate no advantage of common or civil law. The results of the larger bandwidth are evenly split between common and civil law (four negative and four positive coefficients), although the only coefficients with p-values less than 0.05 are negative (indicating a small civil law advantage).

Robustness check (f) includes all areas near the border, not just those inhabited by partitioned ethnicities. This robustness check examines external validity, while, of course,

Table 7: Robustness Checks I

Outcome	Model 1 Light	Model 2 Light Per Capita	Model 3 Electricity	Model 4 Height	Model 5 Floor	Model 6 Sanitation	Model 7 Cell Phone	Model 8 Transport
				(a) Core Specification				
Local Linear Est.	0.012	-1.026	-0.028	-0.053	-0.008	0.023	0.015	-0.072
Robust CCT								
95% CI	0.000, 0.042	-1.202, 0.239	-0.080, 0.046	-0.959, 0.105	-0.098, 0.070	-0.068, 0.146	0.16, 0.141	-0.128, -0.046
Robust CCT p	0.045**	0.003***	0.589	0.115	0.743	0.476	0.014**	0.000***
Wild Bootstrap								
95% CI	-0.028, 0.050	-2.088, -0.596	-0.069, 0.051	-1.121, 0.831	-0.146, 0.085	-0.213, 0.170	-0.084, 0.095	-0.126, 0.031
Wild Bootstrap p	0.479	0.341	0.656	0.713	0.644	0.816	0.694	0.220
Local Quadratic Est.	0.021	-0.712	-0.019	-0.465	-0.021	0.040	0.088	-0.091
Robust CCT								
95% CI	-0.022, 0.066	-1.418, -0.553	-0.091, 0.049	-0.636, 0.9211	-0.074, 0.103	-0.061, 0.128	-0.020, 0.165	-0.093, 0.022
Robust CCT p	0.331	0.000***	0.556	0.720	0.749	0.488	0.012**	0.225
Wild Bootstrap								
95% CI	-0.004, 0.052	-1.582, 0.508	-0.101, 0.094	-1.579, 0.540	-0.165, 0.070	-0.212, 0.210	-0.070, 0.267	-0.164, 0.000
Wild Bootstrap p	0.111	0.332	0.969	0.307	0.552	0.981	0.272	0.049**
Observations	1,145,701	147,483	135,794	30,548	135,682	135,478	87,000	136,320
				(b) Core Specification with Covariates				
Local Linear Est.	-0.004	0.071	-0.019	-0.083	-0.031	0.031	-0.005	-0.088
Robust CCT								
95% CI	-0.010, 0.027	-0.358, 0.936	-0.082, 0.056	-1.248, 0.223	-0.134, 0.059	-0.096, 0.152	-0.014, 0.129	-0.133, -0.060
Robust CCT p	0.355	0.381	0.719	0.172	0.450	0.659	0.117	0.000***
Wild Boostrap CI	-0.043, 0.049	-0.688, 0.920	-0.057, 0.078	-1.053, 0.835	-0.106, 0.083	-0.228, 0.179	-0.119, 0.109	-0.125, 0.067
Wild Bootstrap p	0.971	0.750	0.722	0.844	0.801	0.902	0.303	0.454
Local Quadratic Est.	0.009	0.291	-0.017	-0.555	-0.046	0.026	0.063	-0.101
Robust CCT								
95% CI	-0.032, 0.050	-0.467, 0.566	-0.103, 0.044	-0.725, 1.138	-0.123, 0.077	-0.065, 0.152	-0.030, 0.141	-0.111, -0.007
Robust CCT p	0.670	0.852	0.437	0.665	0.656	0.430	0.203	0.025**
Wild Bootstrap CI	-0.008, 0.028	-0.611, 1.249	0.077, 0.120	-1.379, 0.245	-0.115, 0.052	-0.223, 0.208	-0.085, 0.272	-0.125, 0.067
Wild Bootstrap p	0.263	0.499	0.672	0.844	0.617	0.923	0.307	0.454
Observations	1,145,701	147,483	135,794	30,548	135,682	135,478	87,000	136,320
				(c) Common Law - French Civil Law Border Pairs Only				
Local Linear Est.	0.003	-0.226	-0.003	-0.472	-0.012	0.090	-0.013	-0.108
Robust CCT								
95% CI	-0.017, 0.038	-0.450, -0.157	-0.119, 0.033	-1.156, -0.444	-0.181, 0.094	-0.052, 0.171	-0.062, 0.097	-0.170, -0.119
Robust CCT p	0.453	0.000***	0.269	0.000***	0.534	0.296	0.668	0.000***
Wild Btstrp.								
95% CI	-0.057, 0.059	-0.485, 0.153	-0.138, 0.171	-1.749, -0.259	-0.177, 0.172	-0.079, 0.360	-0.272, 0.122	-0.173, 0.218
Wild Btstrp. p	0.924	0.162	0.535	0.000***	0.859	0.277	0.500	0.754
Local Quadratic Est.	0.011	-0.305	0.023	-0.832	-0.050	0.054	0.019	-0.149
Robust CCT								
95% CI	-0.039, 0.059	-0.570, -0.007	-0.179, 0.166	-1.106, 0.285	-0.245, 0.093	-0.077, 0.191	-0.096, 0.165	-0.187, -0.098
Robust CCT p	0.697	0.045**	0.941	0.247	0.378	0.408	0.603	0.000***
Wild Btstrp.								
95% CI	-0.012, 0.044	-0.508, 0.063	-0.217, 0.177	-2.316, -0.141	-0.243, 0.081	-0.130, 0.272	-0.226, 0.100	-0.202, 0.120
Wild Btstrp. p	0.381	0.075*	0.934	0.031**	0.508	0.429	0.500	0.441
Observations	613,137	43,903	49,590	23,224	49,531	49,423	18,048	50,051

Note: $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.10$. Estimates follow the form of Equation 1. All specifications rely on a uniform kernel. Cattaneo, Calonico & Titiunik (CCT) robust confidence intervals, and p-values are utilized in the first three rows of each panel. Confidence intervals and p-values utilizing a wild bootstrap are in the lower two rows of each panel. Standard errors are clustered at the country level. The treatment indicator, T_i, is equal to 1 for the common law side of the border.

Table 8: Robustness Checks II

Outcome	Model 1 Light	Model 2 Light Per Capita	Model 3 Electricity	Model 4 Height	Model 5 Floor	Model 6 Sanitation	Model 7 Cell Phone	Model 8 Transport
(a) Core Specification								
Local Linear Est.	0.012	-1.026	-0.028	-0.053	-0.008	0.023	0.015	-0.072
Robust CCT								
95% CI	0.000, 0.042	-1.202, 0.239	-0.080, 0.046	-0.959, 0.105	-0.098, 0.070	-0.068, 0.146	0.16, 0.141	-0.128, -0.046
Robust CCT p	0.045**	0.003***	0.589	0.115	0.743	0.476	0.014**	0.000***
Wild Bootstrap								
95% CI	-0.028, 0.050	-2.088, -0.596	-0.069, 0.051	-1.121, 0.831	-0.146, 0.085	-0.213, 0.170	-0.084, 0.095	-0.126, 0.031
Wild Bootstrap p	0.479	0.341	0.656	0.713	0.644	0.816	0.694	0.220
Local Quadratic Est.	0.019	-0.712	-0.019	-0.465	-0.021	0.040	0.088	-0.091
Robust CCT								
95% CI	-0.035, 0.071	-1.418, -0.553	-0.091, 0.049	-0.636, 0.9211	-0.074, 0.103	-0.061, 0.128	-0.020, 0.165	-0.093, 0.022
Robust CCT p	0.503	0.000***	0.556	0.720	0.749	0.488	0.012**	0.225
Wild Bootstrap								
95% CI	-0.004, 0.052	-1.582, 0.508	-0.101, 0.094	-1.579, 0.540	-0.165, 0.070	-0.212, 0.210	-0.070, 0.267	-0.164, 0.000
Wild Bootstrap p	0.111	0.332	0.969	0.307	0.552	0.981	0.272	0.049**
Observations	1,145,701	147,483	135,794	30,548	135,682	135,478	87,000	136,320
(d) 50 Kilometer Bandwidth								
Local Linear Est.	0.019	-0.811	-0.006	-0.090	0.046	0.043	0.102	-0.068
Robust CCT								
95% CI	-0.035, 0.071	-1.407, -0.447	-0.075, 0.100	-0.908, 0.579	-0.044, 0.134	-0.001, 0.187	0.003, 0.179	-0.095, 0.017
Robust CCT p	0.503	0.000***	0.783	0.664	0.326	0.053*	0.044**	0.175
Wild Btstrp.								
95% CI	-0.009, 0.054	-1.643, 0.313	-0.079, 0.076	-1.014, 0.905	-0.047, 0.087	-0.192, 0.145	-0.058, 0.259	-0.141, 0.042
Wild Btstrp. p	0.234	0.309	0.922	0.772	0.465	0.873	0.208	0.276
Local Quadratic Est.	0.018	-0.928	0.009	-0.183	0.044	0.097	0.090	-0.035
Robust CCT								
95% CI	-0.046, 0.076	-1.434, -0.429	-0.024, 0.168	-1.443, 0.896	-0.055, 0.161	-0.041, 0.229	-0.041, 0.249	-0.120, -0.016
Robust CCT p	0.638	0.000***	0.141	0.647	0.336	0.173	0.159	0.011**
Wild Btstrp.								
95% CI	-0.049, 0.082	-1.854, 0.245	-0.073, 0.070	-1.014, 0.905	-0.057, 0.091	-0.193, 0.152	-0.067, 0.255	-0.137, 0.042
Wild Btstrp. p	0.528	0.225	0.939	0.777	0.502	0.875	0.190	0.256
Observations	648,155	80,097	76,864	18,309	76,814	76,671	51,339	77,176
(e) 200 Kilometer Bandwidth^{+}								
Local Linear Est	0.074	-1.641	-0.004	-0.378	0.029	0.015	0.028	-0.075
Robust CCT								
95% CI	-0.048, 0.085	-2.005, -0.799	-0.099, 0.012	-0.939, 0.660	-0.057, 0.062	-0.132, 0.042	-0.039, 0.044	-0.087, -0.033
Robust CCT p	0.585	0.000***	0.125	0.732	0.930	0.308	0.910	0.000***
Wild Btstrp.								
95% CI	0.007, 0.156	-2.910, 0.376	-0.062, 0.094	-1.624, 0.248	-0.038, 0.087	-0.212, 0.213	-0.080, 0.152	-0.134, 0.066
Wild Btstrp. p	0.031**	0.262	0.599	0.141	0.346	0.932	0.663	0.276
Observations	2,201,792	244,616	190,567	49,068	190,424	190,190	113,436	192,435
(f) Entire Border (Including Non-Partitioned Ethnicities)								
Local Linear Est	0.015	-1.017	0.025	-0.053	0.039	0.060	0.043	-0.077
Robust CCT								
95% CI	-0.005, 0.038	-1.192, -0.240	-0.069, 0.059	-0.959, 0.105	-0.074, 0.091	-0.042, 0.151	0.032, 0.148	-0.125, -0.047
Robust CCT p	0.138	0.003***	0.881	0.115	0.837	0.269	0.002***	0.000***
Wild Btstrp.								
95% CI	-0.022, 0.052	-2.074, 0.512	-0.059, 0.125	-1.110, 0.815	-0.122, 0.160	-0.170, 0.197	0.055, 0.092	-0.129, 0.037
Wild Btstrp. p	0.382	0.366	0.567	0.714	0.346	0.893	0.255	0.229
Local Quadratic Est	0.016	-0.708	0.025	-0.053	0.039	0.060	0.043	-0.077
Robust CCT								
95% CI	-0.025, 0.065	-1.408, -0.534	-0.069, 0.059	-0.959, 0.105	-0.074, 0.091	-0.042, 0.151	0.032, 0.148	-0.125, -0.047
Robust CCT p	0.383	0.000***	0.881	0.115	0.837	0.269	0.002**	0.000***
Wild Btstrp.								
95% CI	-0.010, 0.047	-1.558, 0.442	-0.083, 0.105	-1.593, 0.508	-0.191, 0.193	-0.170, 0.197	0.052, 0.263	-0.159, -0.001
Wild Btstrp. p	0.248	0.352	0.848	0.293	0.891	0.893	0.220	0.043
Observations	1,368,211	161,341	150,192	30,548	150,054	149,863	91,378	151,161

Note: $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.10$. Estimates follow the form of Equation 1. All specifications rely on a uniform kernel. Cattaneo, Calonico & Titiunik (CCT) robust confidence intervals, and p-values are utilized in the first three rows of each panel. Confidence intervals and p-values utilizing a wild bootstrap are in the lower two rows of each panel. Standard errors are clustered at the country level. The treatment indicator, T_i, is equal to 1 for the common law side of the border.

$^{+}$ We experienced some issues with invertibility with the local quadratic specification at this bandwidth and could not obtain results. We are currently investigating the issue.

losing some comparability by introducing differences in the ethnicities on different sides of the borders. Ten of the sixteen coefficients are positive, indicating a slight common law advantage, although only one of variables with a positive coefficient (Cell Phone) has p-values less than 0.05, whereas two variables with negative coefficients (Light per Capita and Transport) have p-values less than 0.05.

Overall, the robustness checks confirm that neither common law nor civil law has a consistent advantage. The coefficients are nearly equally split between positive (common law advantage) and negative (civil law advantage). The only variables with p-values nearly always less than 0.05 are Transport and Light per Capita. Both have consistently negative coefficients suggestive of a civil law advantage for these outcomes. Although Light and Cell Phone had positive coefficients with p-values less than 0.05 in the preferred specification, those results are less robust.

6 Caveats and Limitations

Although the empirical strategy deployed in this article has notable strengths, it is also important to discuss its weaknesses and limitations.

It is possible that legal origin makes a difference only for major urban areas, which are generally far from the border. If this is the case, then regression discontinuity would underestimate or completely fail to detect the positive effect of the common law. While this is possible, it also seems implausible. The last forty years of Chinese economic history show the importance of property rights and incentives for economic development in rural as well as urban areas. If the common law was really better at securing property rights and providing free-market incentives, the effects should be apparent in rural as well as urban areas.

It is also possible that legal origin is not important for Africa because, from colonial times to the present, customary and Islamic law have remained important parts of the legal system. While this is true, it is also true for nearly all of the world except Europe and the settler colonies, such as the United States and Australia. Proponents of the legal origin hypothesis have argued for its near universal application, and an argument that it does not apply where customary or Islamic law are important would sharply limit the relevance of legal origin. In addition, it is notable that Anderson (2018) found effects of legal origin even in border areas.

An explanation related to the prior two is that governments in most of Africa are so weak that official law has little effect outside the capital or major urban centers. In those areas, customary law, Islamic law, and informal institutions dominate. This would suggest that our analysis is not capturing the effect of common or civil law, because those laws are not really enforced near the border. This explanation would be consistent with Michalopoulos and Papaioannou (2014), who find that governmental institutions decline in influence when distance from the capital increases. On the other hand, as just mentioned, Anderson (2018) finds effects of legal origin on property rights and HIV even close to the border.

It is also possible that spillover effects mute the effect of legal origin when measured at the border. Perhaps the common law truly leads to superior outcomes, but these superior outcomes generate positive externalities for neighboring regions of civil law countries. While this is possible, it would suggest that the benefit of the common law would become apparent (or stronger) at wider bandwidths, which is not something we observe.

Finally, the regression discontinuity approach assumes that each section of a country has an economic trajectory relatively unaffected by the geographic features of other parts of the country. So, it is assumed that the fact that most of Niger is in the Sahara does not drag down the performance of the wetter parts of Niger near the Nigerian border, and the fact that Nigeria has ports on the Atlantic ocean whereas Niger does not is assumed not to affect areas close to the Niger-Nigerian border. To some degree, these assumptions must be false. Yet it should be noted that they largely bias results towards finding a positive common law effect, because, as a result of Britain's military dominance and ability to largely choose its colonies, common law counties, like Nigeria, are less likely to be landlocked and are more likely to have large natural resource endowments. The fact that we find little or no positive common law effect in spite of this issue reinforces the strength of our conclusions.

7 Conclusion and Future Research

Our research design offers a number of important advantages over the extant literature. First, in contrast to cross-national regressions, we are able to account for a number of factors, many unobservable, by focusing on areas close to the border, where conditions are likely to be similar. Second, by using rich geographical data, we are able to directly control for observable differences across borders. Third, we use light intensity and survey data as a proxies for economic development; these variables are likely to be more accurate than official economic data for Africa, because most poor countries lack the expertise and administrative capacity to measure economic performance precisely. Fourth, by focusing on areas where the same ethnicity straddles the border, we can hold culture constant.

We find little support for the idea that common law legal origin led to superior economic performance. The results are inconsistent, sometimes showing a common law advantage, sometimes showing a civil law advantage, and usually showing no statistically significant difference at all. The strongest results – such as for Transport and Light per Capita – suggest that economic conditions are better in civil law countries. Nevertheless, the confidence intervals for most variables are sufficiently wide that we cannot definitely rule out the possibility that common law has a positive effect.

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