Impact of Chinese Infrastructure Aid on Education: Evidence from Kenya

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1 Introduction

Infrastructure development has long been recognized as a key driver of economic growth and social progress. China has emerged as a major player in financing infrastructure projects across the globe in recent years, especially in Sub-Saharan African (SSA) countries (Huang 2016). The majority of Chinese aid targeted towards SSA regions was allocated to the following 8 countries: Ethiopia, Ghana, Kenya, Namibia, Nigeria, Tanzania, Uganda, and Zambia (Guo, An and Jiang 2022). To study the social impact of China-aided infrastructure projects in SSA countries, this paper leverages the data available in Kenya and combines its Demographic and Health Surveys (DHS) and geocoded Chinese-aid data to investigate the causal impact of China-aided infrastructure projects on the access and equality of education in Kenya.

This research chooses to focus on studying the impact of Chinese aid on Kenya's educational outcomes for two reasons. Firstly, despite many recent reforms and achievements in Kenya and other SSA countries' education, there is still a significant margin for potential improvements when compared to the educational attainments of the rest of the world. Therefore, it is important to understand the potential forces that drive households in Kenya to invest in their children's education. A better understanding of how foreign aid and infrastructure development affect education decisions and outcomes can have useful policy implications in the future. Secondly, previous literature has been focusing on the impact of foreign aid on people's economic life, including income and consumption patterns, poverty reduction, savings rate, and employment rate (Asiedu 2014, Zhang, Zhuang, Ding and Liu 2023, Xu, Zhang and Li 2023, Guo et al. 2022), but the impact of infrastructure aid on education in Kenya and other SSA countries is not well studied yet.

Therefore, the purpose of this paper is to find empirical evidence on how Chinese infrastructure aid projects affect educational access and equality in Kenya, which may suggest some policy implications of how infrastructure construction more broadly can help promote educational achievement and equality in SSA regions. This study analyzes the impact of both educational aid (e.g. building schools and classrooms) and non-educational aid (e.g. aid to transportation, water and sanitation, and health infrastructures) on Kenya's education because different types of infrastructure aid may affect educational outcomes through different channels. For instance, direct educational aid like building a new school in a rural village may incentivize households in that area to send children to school more often because education is now more accessible and available. In addition, a non-educational aid, for example, a new road construction project, can create temporary work opportunities for the locals (Guo et al. 2022), which may allow them to have higher income so that it is no longer necessary for their children to work and they may instead focus on education. Households experiencing income shock due to foreign aid may also have stronger financial capabilities to afford school fees. Furthermore, temporary employment opportunities can allow individuals to gain social experience and foster connections beyond their local community. This exposure may consequently help them understand the substantial returns possible from pursuing education.

In this research, I used difference-in-difference by exploring the fact that different counties in Kenya received Chinese aid at different times while also controlling for aid to Kenya that is not from China. However, both the core regression result and robustness check do not show a significant causal effect of Chinese infrastructure aid on the average years of education received among people aged 19-27 in Kenya. The analysis is also unable to draw statistically significant conclusions on the impact of Chinese aid on the Gini coefficient of the distribution of education level–a proxy of educational inequality–in different counties of Kenya.

The rest of the paper will unfold as follows: Section 2 covers background and motivation, with 2.1 focusing on education in Kenya, and 2.2 on foreign aid to Sub-Saharan Africa. Section 3 introduces the datasets used, while Section 4 outlines our identification strategy. Section 5 presents summary statistics, and Section 6 details the econometric specification of our difference-in-difference strategy. Section 7 reports the main results, followed by robustness checks in Section 8. The paper ends with a discussion and conclusion in Sections 9 and 10, respectively.

2 Background and Motivation

To provide a solid foundation for this research, it is important to understand the education system in Kenya and its ongoing challenges. Additionally, it is crucial to explore how previous research has examined the effects of foreign aid on infrastructure. The motivation for this study is twofold: firstly, the ongoing, significant issues that pervade the Kenyan education sector, and secondly, the limited investigation of the impact that foreign aid exercises on education.

2.1 Education in Kenya

The Kenyan education system currently uses a Competency-Based Curriculum launched in 2017. However, since the publicly available data on infrastructure aid to Kenya is up to 2014, it is also important for us to understand Kenya's education system prior to its most recent reform. Before

2017, Kenya's education follows an 8-4-4 structure, involving eight years of primary education, four of secondary, and four at university. Entry to grade 1 requires a minimum age of 6, and primary education culminates in a mandatory national exit exam, the Kenya Certificate of Primary Education.

There has been tremendous progress achieved in Kenya's education in the past 20 years. In 2003, Kenya initiated the Free Primary Education (FPE) program, canceling school fees across all public primary schools. This endeavor was followed, in 2008, by the implementation of free secondary education. Lucas and Mbiti (2012) discovered that FPE increased the enrollment rate in primary school, spurred the graduation rate, and promoted access for students from underprivileged backgrounds. According to The World Bank, the number of students enrolling in primary school in Kenya has increased 61% from 2000 to 2016, while the total population has only increased by 55% during such period.

However, there are many remaining challenges in Kenya's education if we compare it, along with other SSA countries, to the rest of the world. Specifically, Table 1 presents data from the World Bank, comparing college enrollment rates and adult literacy rates across various regions at their 2020 level. The enrollment rate for college-level education in Kenya and SSA are both 30 percentage points below the world average, and the average adult (age above 15) literacy rate in both regions is also significantly lower than the world average.

Not only does the average level of education in SSA countries lower than the global average, but the distribution of education within these countries has also worsened compared to the rest of the world (Obasuyi and Rasiah 2019). Additionally, the significant inequality in educational achievements and earnings is believed to perpetuate a harmful cycle that results in reduced well-being and limited economic progress (Obasuyi and Rasiah 2019). Moreover, delayed entry, grade repetition, and dropouts are still very common in Kenya (Lucas and Mbiti 2012). Despite the anticipation of substantial gender disparities in education in Kenya, the situation isn't as dire, with school enrollment figures showing that 64% of all females and 66% of males have been enrolled, according to World Bank data from 2019. Likewise, in the broader context of Sub-Saharan Africa, the gender balance in education is almost even. According to World Bank data in 2020, 28% of the total male population and the same percentage of the total female population are enrolled in schools. Nevertheless, given these remaining challenges, it is important for the research community to better understand how the status of education in Kenya and other SSA countries is affected by policies, so as to identify effective strategies for improving education outcomes and closing the gap

Region	Enrollment Rate in College-Level Education	Adult Literacy Rate
Kenya	10%	83%
Sub-Saharan Africa	10%	67%
East Asia & Pacific	51%	96%
South Asia	26%	73%
Europe & Central Asia	76%	98%
North America	87%	99%
Latin America & Caribbean	54%	94%
World	40%	87%

Table 1: Comparison of College Enrollment and Adult Literacy Rates across Regions in 2020

with the rest of the world.

2.2 Foreign Aid To Sub-Saharan Africa

Foreign aid inflows to Sub-Saharan Africa have been increasing since the 1960s, with the region's share in the world's total aid inflows increasing from 14% in 1960 to around 30% in 2017 (Jena and Sethi 2020). China has been a major contributor, with Chinese financiers signing $160 billion worth of loan commitments with African governments between 2000 and 2020, primarily in transportation, power generation, mining, and telecommunications. The top loan recipient countries over the last 20 years included Angola, Zambia, Ethiopia, Kenya, Nigeria, and Cameroon, and most recently the largest recipients included Ghana and South Africa (Foreign Affairs Committee 2022).

Given the enormous, increasing scale of aid to SSA countries, it is therefore important to understand its impacts on the well-being of the recipient communities of such aid. Previous literature has studied the impact of foreign aid on economic growth (Asiedu 2014, Tait, MA, and Chatterjee 2015), poverty reduction (Zhang et al, 2023), nutrition improvement (Xu, Zhang, and Li 2023), and local employment (Guo, An, and Jiang 2022). However, the impact of foreign aid on education in SSA countries is less well-explored.

For example, Guo, An and Jiang (2022) discovered that Chinese infrastructure aid have a positive impact on local employment in African countries, with a two-percentage-point increase in the probability of employment in areas near the aid project compared to areas without aid projects. In their work, they used the geo-coded aid information from AidData, a public dataset maintained by the research lab at Williams & Mary, and matched them with the clusters from the Demographic and Health Survey. By matching these two datasets, the authors were able to create treatment and control groups based on the timing of aid received by each cluster, enabling them to construct a difference-in-difference regressor to estimate the causal effects. This methodology has been directly incorporated into my research, despite differences in the specific outcome variable studied.

The paper by Riddell and Nino-Zarazua (2014) is more directly related to my research in that they studied the impact of foreign aid to education on educational attainment. They have found that direct aid to education expands the enrollment of especially basic education, but its contribution towards increased *quality* of education remains questionable. In addition, they only focused on the impact of aid directly dedicated to education. Given these limitations, my research aims to explore the impact of foreign infrastructure aid, both educational and other types, on a more diverse collection of educational metrics, hoping to obtain a more complete measure of the effect of foreign infrastructure aid on the quality and equality of education outcomes, instead of only focusing on enrollment rates.

Specifically, my research will investigate the change in the average level of educational achievement (years of education completed) and that of its distribution (gini coefficient of years of education completed in a certain population). Additionally, it extends Riddell and Nino-Zarazua's work by examining both education-specific aid and broader types of aid, including transportation, storage, health, emergency assistance, water supply, sanitation, energy generation, communications, and other social infrastructures. This is for two primary reasons. Firstly, educational attainment may be indirectly influenced as infrastructural aid enhances individuals' income, living conditions, and health. Better infrastructure can also reduce the cost of attending school. For example, if poor road conditions impose challenges for parents to send children to school in a reasonable time, constructing new roads can significantly cut transportation costs, which incentivizes parents to send children to school more often. Hence, it is crucial to evaluate the impact of non-educational aid on education. Secondly, potential synergy effects may exist between educational aid and non-educational aid. For instance, combining improved transport systems with increased classroom availability may significantly boost school attendance rates. This synergistic effect may surpass the individual impacts of each intervention.

Overall, my research is motivated by the fact that despite the educational progress in Kenya and other SSA countries, major challenges persist, particularly compared to global standards. Also, there is a lack of comprehensive research regarding foreign infrastructure aid's impact on education in SSA countries.

3 Datasets

This paper uses the following three datasets:

1. Geocoded Global Chinese Official Finance Dataset (Version 1.1.1) (Bluhm et al. 2018, Dreher et al., AidData Research and Evaluation Unit 2017): published and maintained by AidData research lab at William & Mary's Global Research Institute. This dataset contains all the Chinese aid projects globally between 2000 and 2014. There are a total of 123 projects whose recipient is Kenya. For every piece of aid, the dataset provides essential information, including the project id, longitude and latitude coordinates, impacted regions, specific aid categories such as transportation or education, aid titles, the total amount of aid given in 2014 USD, donor details, and the starting year of the project.

2. The 1998 Kenya Demographic and Health Survey (DHS)(NCPD and International 1999): a nationally representative survey that provides information on fertility, family planning, education, and knowledge and behaviors related to sexually transmitted diseases. The survey was a cross-sectional dataset that collected information from 7,881 women and 3,407 men via a two-stage, stratified sampling approach that is able to produce reliable data at the district level. The sampling procedure involves a random selection of "clusters" and then the selection of households within those sampled clusters. Due to the selection process, where men are interviewed only if they are in the household of a selected female, it caused a notable imbalance in the number of male and female respondents.

3. The 2008-2009 Kenya Demographic and Health Survey(KNBS 2010). In this round, the data collects information from 8,444 female and 3,465 male individuals. This DHS survey follows a similar sampling approach as the one done in 1998.

3.1 Data Preprocessing

Two important preprocessing steps are required before working with these three datasets.

Firstly, it is important to note the province-district system utilized in the two DHS datasets is no longer employed in Kenya as of 2013, as it was replaced by the new county system. The 1998 Kenya DHS targeted the following 17 districts: Bungoma, Kakamega, Kericho, Kilifi, Kisii, Machakos, Meru, Murang'a, Nakuru, Nandi, Nyeri, Siaya, South Nyanza, Taita-Taveta, Uasin Gishu, Nairob, and Mombasa. Fortunately, these 17 districts targeted in the 1998 DHS have one-to-one mapping with the current administrative division system's counties. Hence, I converted all 17 districts to their respective counties in the current system.

In the 2008-09 DHS dataset, the specific district to which each surveyed individual belongs is not directly provided. Instead, the dataset includes the geographical coordinates of each sampled cluster. To address this, I utilized a Python script with the Google Maps API to convert the geographic coordinates of each cluster to the corresponding county within Kenya's current administrative division system. Using the cluster-county pairs obtained, I then retrieve the cluster ID of each surveyed individual to match their row of data with the county they reside in.

Secondly, both rounds of DHS surveyed female respondents of age 15-49 and males of age 15-54. It is reasonable to assume that people older than a certain age are unlikely to attend school again, even if education becomes more accessible and rewarding, for example. In my research, I assume that people who are older than 18 will not react to the treatment.

Considering that the first infrastructure project from China to Kenya in my dataset was completed in 2000 and the post-treatment data comes from a 2008-09 survey, then if we assume that people stay in school until they are 18, only people aged 27 and younger in 2008/09 would have been in school between 2000 and 2008/09. Therefore, I restrict the post-treatment sample to people aged 15 to 27 in the 2008-09 survey. In order to make the pre-treatment level data comparable to the post-treatment sample, I impose the same age restriction on the 1998 DHS dataset. Although implementing age restrictions results in losing some observations, it is a worthwhile step as it allows for easier identification of signals when examining people who are more likely to react to the treatment.

3.2 Limitation

There are several shortcomings in my selected datasets, and these shortcomings have various degrees of effects on the confidence level of the results, which I still now discuss in detail.

First, due to the fact that the datasets only record educational information for people older than 19 years old, we might underestimate the positive effects of infrastructure construction on enrollment rate. In Kenya, the average national level primary school enrollment rate is only around 50%, which indicates a huge potential to increase the primary school enrollment rate(Odebero, Maiyo and Mualuko 2007). However, we only have education data for people older than 19 in 1998 and 2008-09. Therefore, children who are under 6 years old that were about to enter primary school education a few years after 1998 will be around 10 to 16 years old in 2008. Hence, a large part of the causal impact of the treatment on the primary school enrollment rate is not identifiable.

Second, AidData only records aid from China to Kenya, but it does not contain information on how much aid Kenya received from other countries between 1998 and 2008. Therefore, the reliability of the final causal estimate will heavily rely on the parallel-trend assumption in difference-in-difference. Reasons to believe such an assumption will be explained in detail in Section 5.

Third, due to the nature of the DHS study, men are interviewed only if they belong to the household of a female interviewee, which means that male respondents are not selected fully at random. Single men are not included in the survey, and a large portion of single males are young people aged between 20 and 30. Males in that age group in 2008 will be around the age for secondary or college-level education, but much of their education information will not be recorded by the DHS study. Therefore, we may proportionally have fewer young men compared to women in our datasets, resulting in an underestimate of the causal effect of infrastructure construction on men's educational outcomes. In addition, there is also the issue of confounding due to data missing not at random. For example, one could argue that smarter and wealthier men are both more attractive to women and have a better chance to complete more years of education. If so, the male sample in the DHS dataset would be an overestimate of the educational level among young men. It is very challenging to estimate which of the two opposite forces is dominant in this situation.

Finally, the DHS dataset only records the highest level of education (primary, secondary, or advanced/college level) and the highest grade *reached* at that level for each respondent. However, reaching a certain grade is not equivalent to completing that grade level. For example, the data does not allow us to distinguish the difference between people who have fully completed grade 8 with those who attended grade 8 for a week but then decided to drop out. Therefore, the DHS dataset provides an overestimate of the actual number of years of education completed, as I convert these grade level information into the length of education someone receives in my downstream analysis.

Although my selected datasets have various limitations, the DHS data is the only available dataset on Kenya education that would allow me to study the causal impact of Chinese aid projects. The timing of the surveys is crucial because my treated and control group are constructed using the fact that different counties in Kenya received aid from China for the first time in different years. Therefore, I need two survey datasets, one that offers the outcome variable at the pre-treatment level and another survey that contains post-treatment outcome variable. Since the timing of AidData is between 2000 and 2014, the first survey needs to be conducted right before 2000 and the second survey should ideally allow me to have a balanced amount of data points in the treated and control groups. Given these technical constraints, the DHS datasets are the best available despite their limitations.

4 Identification Strategy

The goal of this research is to identify the causal effects of Chinese infrastructure aid projects on education achievement and equality in Kenya. Specifically, there are two outcome variables of interest: the average length (in years) of education received by Kenyan women of age 19-49 (and men of age 19-54) and the Gini coefficient of the distribution of the length of education received among the population living in the treated counties.

Given this goal, the most naive identification strategy would be to simply label all counties that received aid from China between 2000-2014 as treated and mark the rest as control. Then, one can compare the difference in the change in the average length of education between the treated and control group. However, such difference is associative, not causal, due to potential confounders that both cause the county to receive aid and improve education enrollments and equality. For example, such a confounder could be population because densely populated counties might receive more aid due to its greater scale of potential benefits, and counties with more population might also have a faster-growing demand to employ people with high education in the job market. In this case, the higher increase in educational achievement in those treated counties might be primarily due to their greater size of population, not due to the infrastructure aid from China.

Hence, it is crucial to design an identification strategy that minimizes the chance of confounding. In this research, I used a difference-in-difference approach by exploring the delays in the administrative process of aid transfers from China to Kenya. For a typical infrastructure aid project, it takes time for both sides of the government or organization to discuss the purpose and details of the project before aid transfer can happen. The process from initiation to execution can take from a few months to a few years. Assuming the length of such delay is random, we can then mark counties that received their first aid from China earlier as the treated group and counties that received their initial aid slightly afterward as the control group.

In addition, the difference-in-difference strategy also assumes that other donors are not changing their funding behaviors in response to where Chinese aid is funded. It is reasonable to make such an assumption because priorities in making foreign assistance are different among different governments. For instance, while the majority of the Chinese aid targets transportation, storage, and energy generation, as shown in Table 2, over 70% of the U.S.'s assistance to Sub-Saharan Africa over the past decade has sought to address health challenges, primarily HIV/AIDS (Husted, Blanchard, Arieff and Cook 2020).

Since the DHS dataset is available for the years 2008-09, I define the treated group as counties that received their initial aid from China between 2000-2008 and the control group as counties that received the initial aid between 2008-2014. By processing the AidData dataset, counties in the treated and control group can be identified:

- Control Counties: Baringo, Kirinyaga, Nakuru, Narok, and Uasin Gishu
- Treated Counties: Kericho, Kiambu, Kisii, Meru, Mombasa, Nairobi, and Nandi

Admittedly, 5 data points in the control group and 7 in the treated group do not allow us to make conclusions with very high statistical confidence. Therefore, at the end of this paper, there is an entire section dedicated to discussing the potential way to use this same research framework to obtain more data points from other SSA countries in order to make stronger causal conclusions.

5 Summary Statistics

Table 2 summarizes aid from China to Kenya between 2000 and 2014 into 13 categories. There are a total of 123 aid projects. 10 ($\approx$ 8.13%) of which are education aid, and the majority of aid does not directly target education. The total amount of aid value focused on education is around 110.21 million USD (deflated in 2014 USD value), which accounts for 1.88% of the total aid value from China to Kenya during that period, while aid to transportation and storage consists of close to 70% of the overall aid value. This category-specific analysis highlights the importance of considering both educational and non-educational aid when evaluating the full impact of Chinese aid projects on Kenya's education, as omitting non-educational aid may risk overlooking a significant indirect influence on the educational sector.

Table 3 summarizes the age and education information in the 1998 DHS study for each of the treated and control county, after imposing age restrictions as described in section 3.1. There are 681 respondents in the control group and 1886 in the treated group, which allows us to interpret the distribution of age and education with high statistical confidence. There are also no statistically significant differences between the average age and years of education between the treated group and control group as a whole, which is evidence supporting my identification strategy.

Category	# of Aid	Aid Value (million USD)	% of Total Aid Value
Transportation and Storage	49	4047.28	69.13
Energy Generation and Supply	17	1080.20	18.45
Health	13	150.69	2.57
Education	10	110.21	1.88
Government and Civil Society	7	320.82	5.48
Emergency Response	6	55.66	0.95
General Environmental Protection	6	21.91	0.37
Agriculture, Forestry and Fishing	4	6.92	0.11
Industry, Mining, Construction	4	27.32	0.47
Population & Reproductive Policies	3	0.74	0.01
Communications	2	N/A	N/A
Action Relating to Debt	1	31.04	0.53
Other	1	1.59	0.03
Total	**123**	**5854.40**	**100**

Table 2: Number and value of aid from China to Kenya per Category, between 2000 and 2014. Aid values are represented in units of million USD (deflated to 2014 USD). N/A indicates missing data.

Similarly, Table 4 summarizes the age and educational information recorded in the 2008-09 DHS study. In other words, this table records post-treatment level of education for the treated and control counties. There are a few striking numbers that are worth discussing.

First, there are only 14 respondents from Narok in the 2008-09 round, so the degree to which that row of number is truly representative of Narok is questionable. Also, Narok seems to only have an average of 1.29 years of education and a 0.93 gini coefficient on education equality. These numbers are drastically different than Narok's figures in 1998 in Table 3. According to the census done in 2019, Narok has over 1.1 million population. Therefore, it is very likely that the difference in Narok's average education level between the two rounds of DHS is due to sampling variability. I will exclude Narok during robustness check to test whether this data point matters for the result.

Second, compared to the pre-treatment level, the post-treatment average length of education of the control group declines from 7.89 years to 7.67 years. However, among the treated group, such number rises from 8.01 year to 9.97 years. This seems to be a significant increase, which gives us some evidence that the causal impact of China-aided infrastructure projects might have a positive causal impact on the average level of education among adults in Kenya. However, we need more statistical tests to examine whether that is a statistically significant difference.

It is also important to note that the means and standard deviations in Table 3 and 4 are computed by treating males and females with different weights. Table 5 provides a concrete example of the gender imbalance issue in our dataset. There are significantly more women than men due to the sampling process of the DHS studies. Therefore, when computing the mean and standard

County	Age_mean	Age_sd	Years_Ed_mean	Years_Ed_sd	Years_Ed_gini	n
Baringo	20.80	3.73	7.17	2.82	0.21	30
Kirinyaga	21.52	3.10	6.52	2.88	0.24	29
Nakuru	21.19	3.61	8.41	2.76	0.18	216
Narok	20.48	3.23	6.44	3.03	0.26	50
Uasin Gishu	20.07	3.66	7.95	2.55	0.18	356
All Control Counties	20.55	3.64	7.89	2.75	0.19	681
Kericho	20.45	3.66	7.76	2.54	0.17	288
Kiambu	20.70	3.45	8.54	2.37	0.15	87
Kisii	20.22	3.76	8.02	2.84	0.20	241
Meru	20.21	3.57	7.06	2.83	0.22	298
Mombasa	21.53	3.51	7.99	3.82	0.26	354
Nairobi	21.11	3.45	9.72	3.04	0.17	312
Nandi	20.73	3.62	7.31	2.60	0.19	306
All Treated Counties	20.75	3.61	8.01	3.11	0.21	1886

Table 3: Demographic and Educational Characteristics of Kenyan Counties in 1998: A Comparison between Control and Treated Counties. The columns are (from left to right): the mean and standard deviation of the respondents' age, the mean and standard deviation of the respondents' number of years of education received, the Gini coefficient of the distribution of the length of education received, and the number of individual respondents from that county/group.

deviation values for each county, we need to assign higher weights to men and lower weights to women based on the percentage of respondents from that county that are male. Specifically, we assign men with weight $1/p_m$ where p_m is the percentage of men in a given context; and women are assigned with weight $1/(1-p_m)$. For example, a male from Kericho in the 1998 DHS study will be assigned the weight $1/0.2639 \approx 3.79$ whereas women will have the weight $1/(1-0.2639) \approx 1.36$. Had we not assigned different weights to different sex, our mean and standard deviation estimates would have been biased.

The formula for calculating the weighted mean of a set of data points, where each data point has a corresponding weight, is $\bar{x}_w = \frac{\sum_{i=1}^{n} w_i x_i}{\sum_{i=1}^{n} w_i}$, where $\bar{x}_w$ is the weighted mean, x_i is the ith data point, w_i is the weight assigned to the ith data point, and n is the total number of data points.

Similarly, the formula for calculating the weighted standard deviation is $S_w = \sqrt{\frac{\sum_{i=1}^{n} w_i (x_i - \bar{x}_w)^2}{\sum_{i=1}^{n} w_i}}$, where S_w is the weighted standard deviation and all other symbols refer to the same meaning as mentioned earlier.

6 Econometric Specification

In this study, we aim to analyze the impact of Chinese infrastructure aid on the following outcome variables: 1) the mean years of education in different counties, and 2) the Gini coefficient of the length of education among people in different counties, both of which are on a continuous scale.

County	Age_mean	Age_sd	Years_Ed_mean	Years_Ed_sd	Years_Ed_gini	n
Baringo	20.43	3.92	5.36	3.96	0.41	47
Kirinyaga	21.11	3.81	8.73	2.29	0.14	90
Nakuru	20.67	3.85	8.03	2.53	0.17	60
Narok	19.93	3.92	0.36	1.29	0.93	14
Uasin Gishu	20.79	3.67	8.50	2.93	0.19	112
All Control Counties	20.76	3.80	7.67	3.42	0.24	323
Kericho	19.65	3.17	8.46	2.75	0.18	57
Kiambu	21.15	3.51	9.55	2.50	0.14	157
Kisii	21.10	3.70	8.86	2.93	0.18	212
Meru	20.72	3.88	8.14	3.05	0.20	152
Mombasa	21.45	3.47	9.49	3.40	0.19	173
Nairobi	21.96	3.32	11.15	4.01	0.20	676
Nandi	21.20	3.34	8.71	2.16	0.13	41
All Treated Counties	21.45	3.52	9.97	3.66	0.20	1468

Table 4: Demographic and Educational Characteristics of Kenyan Counties in 2008-09: A Comparison between Control and Treated Counties

County	Male_Percent
Kericho	26.39
Kiambu	32.18
Kisii	24.90
Meru	32.21
Mombasa	27.68
Nairobi	24.36
Nandi	31.05

Table 5: The percentage of men in each of the treated counties in the 1998 DHS dataset

Specifically, the Gini coefficient is a number between 0 and 1 that measures the degree of inequality, where 0 represents perfect equality (i.e., everyone in the population has the same income, wealth, or education level) and 1 represents perfect inequality (i.e., one person has all the income, wealth or educational experience, and everyone else has nothing).

We use a difference-in-differences (DiD) approach to estimate the causal effect of the treatment on the two outcome variables. The DiD regression model is:

$Y_{it} = \alpha + \beta_1 \cdot is\_treated_{it} + \beta_2 \cdot is\_post\_treatment_{it} + \beta_3 \cdot is\_treated_{it} * is\_post\_treatment_{it} + \beta_4 \cdot has\_other\_donor_{it} + \epsilon_{it}$

where i represents a specific county and t represents the year of observation, which is either 1998 or 2008-09. Y, the outcome variable, is either the average length of education (in years) or the Gini coefficient of the distribution of educational attainment. The three variables that start with *is* are indicator variables that take the value 1 or 0. *has_other_donor* is also a binary variable that indicates whether a county has received aid from donors other than China between 2000 and 2008-

09. In this way, the coefficient of interest, β_3, is able to capture the difference-in-differences effect of having China as an *additional* donor on the two outcome variables, conditioning on whether a county also receives foreign aid from other sources.

Variables Y, $is\_treated_{it}$, and $is\_post\_treatment_{it}$ are found through cross-analysis of AidData and DHS data, and they are already available in table 3 and 4. The control variable $has\_other\_donor_{it}$ is found by analyzing the global version of AidData through its GeoQuery function (Goodman, BenYishay, Lv and Runfola 2019). Specifically, GeoQuery allows me to extract all aid towards different counties of Kenya between 2000 and 2008-09. For each county, a positive value after subtracting the value of all aid from China from the value of all aid indicates the existence of non-Chinese aid to that county during that period, so $has\_other\_donor_{it}$ should be set to 1. Otherwise, $has\_other\_donor_{it}$ equals 0. In my analysis, I found $has\_other\_donor_{it}$ to be 1 for all treated and control counties.

In an ideal situation, we would also want to include other potential confounders to condition on, in order to avoid spurious correlations. Such confounders that affect both treatment and outcome might be, for example, GDP, policy incentives, administrative priorities, and prior relationship with the Chinese government.

However, I choose not to include other additional control variables in this research due limited sample size in our data. Although we have hundreds of observations for each county, a single county only counts as one data point in the DiD regression. As a result, we do not have enough degrees of freedom to include many more additional control variables. This is a limitation of my research.

7 Results

The results of running the regression are presented in Table 6. Among Kenyans aged between 15-27, the treatment's estimated causal impact on the average length of education is an increase of 2.238 years, with a standard error of 1.477 and a 90% confidence interval ranging from -0.309 years to 4.785 years. In terms of the Gini coefficient, the estimated causal impact is -0.175, with a standard error of 0.125 and a 90% confidence interval spanning from -0.391 to 0.040.

However, the results are not statistically significant as the confidence intervals for both outcome variables include 0. This indicates that the treatment's true effect on the average years of education and the Gini coefficient of education distribution might be negligible or even non-existent. It is also possible that the true effect of our treatment on education is significant, but my method cannot

	Estimated	Std Error	90% C.I.
Causal impact on mean years of education	2.238	1.477	[-0.309, 4.785]
Causal impact on gini coefficient	-0.175	0.125	[-0.391, 0.040]

Table 6: Causal impact of treatment on two outcome variables: 1) the average years of education in different counties, and 2) the Gini coefficient of the distribution of length of education received by people in different counties

correctly identify it due to the small sample size. Thus, the current result does not allow us to conclude statistically significant causal effects of China-aided infrastructure projects on Kenya's educational attainment and equality.

Although unable to make significant conclusions, the estimates are indeed in the direction that is beneficial–infrastructure aid increases the average years of education and decreases educational inequality. Also, the 90% confidence intervals are on the edge of crossing 0. This suggests a strong likelihood that, with more data points, we could potentially identify a significant impact of Chinese infrastructure aid on education in Kenya. Hence, I discuss possible ways to continue or extend my research in section 9.

8 Robustness Checks

To ensure the reliability of our findings, I conduct robustness checks by excluding a potentially influential observation, Narok, from the dataset. As I mentioned earlier, the data on Narok is likely to be statistically insignificant and are subject to sampling variability due to the insufficient amount of people interviewed in Narok.

After removing Narok from the analysis, I found that the estimated causal impact on the average length of education changed to an increase of 0.992 years, with a standard error of 0.936 and a 90% confidence interval ranging from an increase of -0.631 years to 2.616 years. In terms of the Gini coefficient, the estimated causal impact was -0.048, with a standard error of 0.051 and a 90% confidence interval spanning from -0.136 to 0.0413.

Similar to the initial analysis, the results of the robustness check still show no statistically significant causal effects of the treatment on both outcome variables, as the confidence intervals continue to include 0. This further confirms the need for additional research and data analysis to draw more definitive conclusions about the treatment's effectiveness on educational attainment and equality in Kenya.

	Estimated	Std Error	90% C.I.
Causal impact on mean years of education	0.992	0.936	[-0.631, 2.616]
Causal impact on gini coefficient	-0.048	0.051	[-0.136, 0.0413]

Table 7: Causal impact of treatment on two outcome variables after removing Narok

9 Discussion

Although both the core identification strategy and robustness checks fail to draw statistically significant conclusions, both regressions yield confidence intervals that are close to crossing 0. This suggests a promising avenue for future work, especially if the research limitations identified in this study can be addressed effectively.

This study is subject to four key limitations. First, it suffers from an insufficiency of data points. The research's scope is confined to just 12 counties in Kenya, with each providing two data points—one pre-treatment and one post-treatment—which is very challenging to apply high-dimensional regression techniques due to insufficient degrees of freedom. Secondly, the study faces challenges in validating its difference-in-differences parallel trend assumption. While I backed my assumption with evidence from the literature–for example, the U.S. and Chinese governments have very different funding priorities–this study does not provide any empirical evidence to support the parallel trend assumption. Thirdly, the treatment variable is binary rather than continuous, that is, this study only considers whether aid from China is present, but it does not take into account the amount of aid received. Therefore, the results have limited granularity. This limitation also applies to the controlled variable *has_other_donor*. Finally, there are confounding factors that the study has neglected to consider, for example, the county's GDP and political stability, which can influence both China's funding plan and the educational outcomes in this study. These overlooked confounders may introduce spurious correlations between the treatment and the outcomes, which may bias our causal estimate toward a more significant direction than its true effects.

Given the scope of this study and the identified limitations, there are several directions to expand this research. First, one may consider expanding the research scope by including countries beyond Kenya. Over the past two decades, China has funded many other SSA countries, for example, Ethiopia, Ghana, and Tanzania. The research framework used in this study–combining geocoded AidData and results from DHS–is widely applicable to these countries, as the DHS program has been collecting and analyzing data through more than 400 surveys in over 90 countries. All these countries mentioned earlier have done many rounds of DHS in the past, and these datasets are all publicly available. Including more countries in future research can yield more data points and allow control for more confounding variables.

Secondly, more rigorous validation of the difference-in-differences parallel trend assumption is desired. Although this study relied on literature for backing this assumption, future work may consider providing empirical evidence that substantiates this assumption. For example, one can fit a regression model that predicts the change in the amount of non-Chinese aid received by a certain county after receiving Chinese aid. If the parallel assumption is valid, the researcher should discover that the quantity of Chinese aid is an ineffective predictor for the shift in the amount of non-Chinese aid.

Finally, considering a continuous treatment variable would significantly improve the granularity of the results. For instance, quantifying the amount of aid received rather than just its presence or absence might offer deeper insights into how to best allocate resources. For example, the effect of Chinese aid on education might be non-linear and have a declining marginal return. Finding empirical evidence of such shape can help the donors improve the efficiency and effectiveness of their donation strategy.

By addressing these limitations, future research can better assess the relationship between infrastructure aid and education in SSA and provide more significant and robust findings.

10 Conclusion

This study examined the impact of Chinese infrastructure aid on educational access and equality in Kenya. Through a difference-in-difference approach, this study found that receiving infrastructure aid from China potentially increases the average length of education among Kenyans aged 15-27 by 2.238 years and decreases the Gini coefficient of the length of education by 0.175, indicating a potential improvement in educational equality. However, these results are not statistically significant, indicating a need for further research to confirm these findings.

Despite the lack of statistical significance, these findings are important for several reasons. Firstly, they contribute to the existing literature on the impact of foreign aid on education, a topic that has not been extensively studied in the context of Sub-Saharan Africa. Secondly, the estimates are in a beneficial direction, suggesting that infrastructure aid increases the average years of education and decreases educational inequality. With more data points, a significant impact could potentially be identified.

Several questions remain for future research. The limitations of this study, including the insufficiency of data points, challenges in validating the difference-in-differences parallel trend assumption, the binary nature of the treatment variable, and overlooked confounding factors, provide opportunities to expand this research in the future. As suggested in section 9, future researchers may consider collecting more data points by including more countries, providing empirical evidence to support the parallel trend assumption, considering a continuous treatment variable, and controlling for more confounding variables. These future directions are highly feasible, as both AidData and the DHS program have plenty of existing data on countries that have been receiving Chinese aid over the past two decades.

In conclusion, while this study does not find statistically significant evidence of the impact of Chinese infrastructure aid on education in Kenya, it does suggest promising directions for future research. By addressing the identified limitations and expanding the scope of the research, future studies may be able to provide more definitive insights into the relationship between infrastructure aid and education in Sub-Saharan Africa.

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