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Chinese Development Assistance and Household Welfare in Sub-Saharan Africa

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Abstract

By combing geocoded project-level data on Chinese development assistance with geocoded household-level data from the Demographic and Health Survey (DHS), we investigate the effect of Chinese project assistance on household welfare in 13 sub-Saharan African countries. We exploit the geographic proximity of household clusters across two different DHS survey waves (before and after the influx of Chinese aid) and use a difference-in-difference design in order to investigate the impact of Chinese aid on households' wealth and education. Our results consistently point to an overall positive effect of Chinese project assistance on household welfare: areas that receive Chinese projects are more likely to be wealthier, stay in school longer, and achieve a higher educational attainment than areas which did not receive such projects. Results are robust to various alternative model specifications.

JEL Classifications: F35, O19, O20
Keywords: OECD-DAC, Aid Allocation, Aid Effectiveness, China, Africa, Emerging Donors, Project Level, Household Welfare, DHS, Geocoded Data

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Contents

1. Introduction

The Diplomat, an international online news magazine, has referred to China's graduation from a poor country to an economic superpower within no less than 30 years as an "earth-shaking rise".[1] Meanwhile, the global community has followed China's development with both hope and anxiety: there is as least as much admiration for China's achievements as there is criticism for its authoritarian leadership style, human rights violations, and aggressive business practices. This also applies to China's new role as an international donor. Formerly a recipient of development aid itself, China is now probably the largest of the so-called emerging donors. Speculations about the repercussions of Chinese foreign assistance on recipient countries are numerous and most notably larger than evidence on its actual consequences (see Naím, 2007). This applies to sub-Saharan Africa especially, where China has ramped up its activities not long after the turn of the millennium.[2]

Until recently, systematically assessing the allocation and effectiveness of Chinese aid has been very difficult, because the Chinese government barely publishes information on its foreign assistance. Fortunately, however, data availability has significantly improved due to a comprehensive dataset on *Chinese Official Finance to Africa* issued by the AidData research lab. Today, a growing body of empirical literature is providing new insights on the drivers of Chinese aid allocation (see Strange et al. 2013, Dreher et al. 2014, Strange et al. 2014, Dreher et al. 2015, Dreher and Fuchs 2015, Strange et al. 2015, Kilama 2016). A study by Isaksson and Kotsadam (2017) moreover looks at the governance aspect of Chinese aid and finds a positive relationship between Chinese aid and local corruption. Research on the effectiveness of China's aid is conducted as well, but to a much lesser degree. Dreher et al. 2016 and Dreher et al. 2017 are the only study we know of that examine and find a positive effect of Chinese aid on growth in recipient countries. In view of China's growing influence as an international donor, it is important to learn more about the poverty reduction potential of its activities.

The present paper investigates the effectiveness of Chinese aid in sub-Saharan Africa (SSA). This region is the poorest in the world, the largest recipient of Chinese aid[3], and a major destination for other forms of economic cooperation from China (Brautigam 2009, Sanfilippo, 2010). More specifically, we analyse

[1] https://thediplomat.com/2011/02/understanding-chinas-global-impact/

[2] See Kobayashi (2008) and Bräutigam (2009) for a discussion of the evolution of Chinese aid since the 1990s.

[3] See the first China White Paper on Foreign Aid published in 2011: http://english.gov.cn/archive/white_paper/2014/09/09/content_281474986284620.htm

if and to what extent Chinese aid projects impact household welfare in 13 sub-Saharan African countries. Since Chinese aid covers a broad range of sectors (Bräutigam 2009, Strange et al. 2014) and potentially affects various dimensions of peoples' lives, we look at two different measures of well-being: wealth and educational outcomes. Both measures are key to household welfare, highly relevant for poverty reduction and relate to sectors in which China is very active. To the best of our knowledge, this is the first study to provide cross-country evidence on the effectiveness of Chinese aid at the micro-level and beyond the dimension of economic growth.

An obvious challenge to our research objective is that we are dealing with non-randomised observational data that is prone to selection bias: Chinese aid projects are unlikely to be randomly allocated across countries and regions within countries. This makes it difficult to obtain reliable estimates of the effect of Chinese aid on household well-being. In order to deal with this problem in the best way possible, we approach our empirical analysis as follows (see also Section 2). We match georeferenced data on Chinese aid projects in the AidData set to georeferenced household data in the Demographic and Health Survey (DHS) at two points in time: before and after the inflow of Chinese aid. Using a difference-and-difference estimator, we then compare the welfare of household clusters that have been "treated" with at least one aid project between the two DHS survey waves to the welfare of "control" clusters. By exploiting the geographic proximity of household clusters covered by the DHS, we are able to compare households located in the same area before and after treatment. This greatly increases the comparability of households in our dataset across time.[4] In addition, we use inverse probability weighting – a matching method – in order to construct a proper counterfactual and make treatment and control clusters as comparable as possible. Since information on the exact number of Chinese projects on the ground as well as their financial project volume is rather patchy, our main analysis captures treatment in form of a dummy variable indicating the presence of a project (yes/no). However, in order to also consider treatment intensity, we extend our analysis by replacing the dummy with the number of projects on the one hand and financial project volume on the other hand.

Our study contributes to two main strands in the aid literature. First, it adds to the empirical literature that investigates aid effectiveness at the sub-national level across countries (see Kilby 2000, Dollar and

[4] Since the DHS survey is not a panel, we cannot compare the same households at two different points in time, namely before and after treatment. However, we can compare households located in *same area* at two different points in time, allowing us to achieve a high comparability between households across survey waves.

Svensson 2000, Guillaumont and Laajaj 2006, Denizer et al. 2013, Bulman et al. 2015, Dreher and Lohmann 2015, Metzger and Günther 2015, Briggs 2016, Kotsadam et al. 2018). Studying aid effectiveness sub-nationally is important, because it helps narrowing the gap between macro- and micro-economic studies in the field (Rodrik 2008, Denizer et al. 2013, Bulman et al. 2015, Metzger and Günther 2015, Dreher et al. 2016, Dreher et al. 2017, Briggs 2018). Second, we add to the (yet) small body of literature on the effectiveness of Chinese aid (Dreher et al. 2016, Dreher et al. 2017). Given the methodology we use, our study also relates to newer literature that applies a difference-in-differences (DiD) approach to geo-referenced and non-randomised observational data (see Kotsadam and Tolonen 2016, Isaksson and Kotsadam 2018, Kotsadam et al. 2018).[5] Yet, we propose an alternative methodology to exploit our geo-referred information which relies on impact evaluation methods to reduce the potential bias due to the lack of a perfect counterfactual.

The existing literature offers few insights on China's aid effectiveness directly, but there are indirectly related aspects worth pointing to. On a positive note, China's South-South cooperation philosophy[6] may lead to higher ownership, larger freedom of choice and, thus, better targeting of aid, rendering foreign assistance more effective. Moreover, China's emphasis on project aid as well as technical cooperation and training can be an effective way to promote local economic development in the short-term (Clemens et al. 2012, Reilly 2015). Last, China's comparatively strong focus on (often big scale) economic cooperation may create direct opportunities for the local population and, at the same time, lead to a better integration of national markets into the global economy. The positive relationship between Chinese aid and regional (Dreher et al. 2016) and national growth (Dreher et al. 2017) lends support to these arguments. On the other hand, China's non-interference and no-strings-attached loan policy can threaten debt sustainability (Kilama 2016) and undermine good governance and foster corruption (Isaksson and Kotsadam 2017). Moreover, the Chinese government's emphasis on mutually beneficial cooperation might affect profit sharing negatively and diminish longer-term economic benefits to recipient countries.

[5] Benyishay et al. (2017) provides a review on how increasingly available disaggregated geospatial data allows for applying a variety of impact evaluation methods to assessing the effectiveness of aid, among others.

[6] China's foreign assistance is guided by eight principles. For details see: http://www.china.org.cn/opinion/2011-11/29/content_24030234.htm

To what extent these considerations affect the welfare of households that live in the proximity of Chinese aid projects is an open question that we explore in this study. Our main results (discussed in Section 3) consistently point to an overall positive impact of Chinese project assistance on the welfare of households living in our sample countries. Areas that receive Chinese projects are more likely to be wealthier, stay in school longer, and achieve a higher educational attainment than areas which did not receive such projects. These findings are confirmed when we break the analysis down to the sector level (Section 4), although we also find some evidence for heterogeneous effects of aid. The latter suggests that a sectoral analysis of aid can be helpful in further unravelling the mechanisms through which Chinese projects affect household welfare. Finally, we find that the intensity of treatment seems to have implications for household welfare: a (positive) non-linear relationship between treatment and outcome variables indicates that positive effects of aid only materialise when certain number of projects (or a certain project volume) is reached. However, these effects seem to wear off in some cases once a certain threshold is passed.

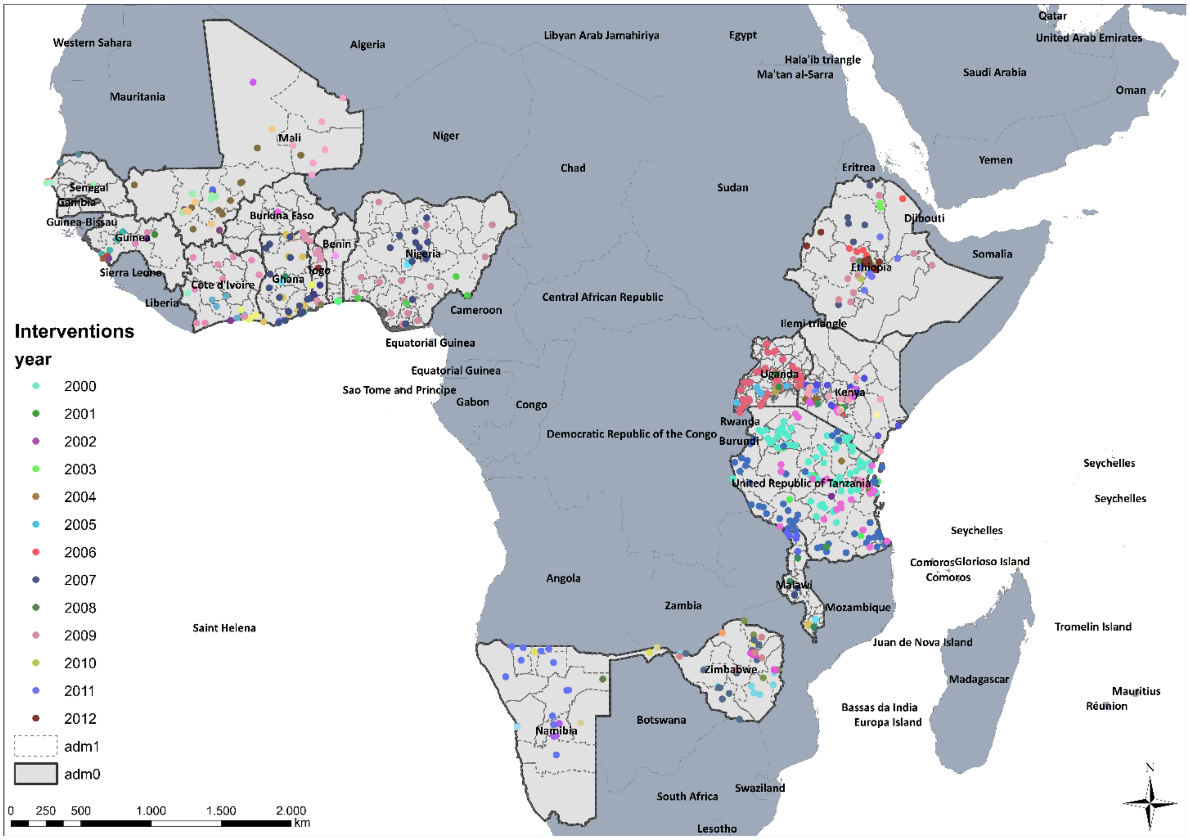
2. Data and Methods

Our analysis is based on the combination of two main sources of data: (1) Aid Data's *Chinese Official Finance to Africa* dataset and (2) the Demographic and Health Survey (DHS). Our sample consists of 13 African countries for which at least two DHS survey waves are available and for which the first wave corresponds to a period characterised by little or no Chinese aid activities (i.e. before the year 2000): Benin, Cote d'Ivoire, Ethiopia, Ghana, Guinea, Kenya, Malawi, Namibia, Nigeria, Senegal, Togo, Uganda and Zimbabwe.

2.1 Aid Data

The *Chinese Official Finance to Africa* dataset comprises 1,955 geocoded projects in 50 African countries, spanning 3,545 locations and covering the years 2000 to 2012. The countries included in our sample account for 852 projects in 1,745 locations, which are widely distributed within countries and across time (see Figure 1).

Figure 1. Mapping of Chinese Aid Projects by Destination Countries



For each project, the database provides detailed information on its location, the sector it belongs to (classified following the OECD Creditor Report System (CSR) purpose codes), its financial volume, the type of flow[7] (e.g. ODA or other official flows, OOF) and its status (e.g. planned or implemented).

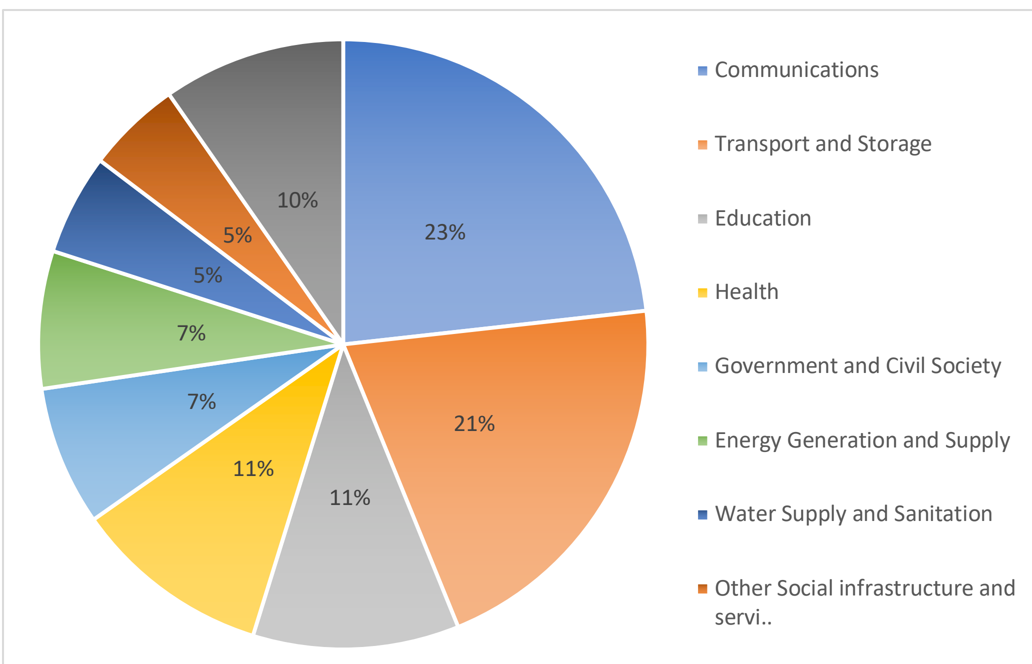
We made two major adjustments to the data for our empirical analysis. First, a large majority (67.4%) of projects are classified either as "completed" or "implemented", while the rest is still "in the pipeline". Projects in the pipeline have not formally started and 11.3% of them are pledged only. Since their implementation is uncertain, we exclude these projects from our analysis. Second, we only account for projects that are defined by a precise location, which is key to the identification strategy adopted in the

[7] In the case of China, it is important to distinguish between official development assistance (ODA)-like flows and other official flows (OOF). According to the DAC definition, ODA is (a) provided by official agencies to developing countries, (b) aimed at promoting economic development and welfare, and (c) contains a grant element of at least 25 percent. OOF are also funded by government agencies, but not primarily aimed at development goals and/or not sufficiently concessional to categorise as ODA. Results from an empirical work by Dreher et al (2015) show that Chinese ODA to Africa are not significantly correlated with national political institutions, while OOF-like flows are more likely to go to countries with higher corruption levels.

rest of the analysis. AidData attributes a precision code to each geo-localised project that identifies how close a project is to a given set of coordinates. We consider projects with a precision code of up to 4, meaning that the project location is at least overlapping with a first order administrative division such as a province, state or governorate.[8] Of the total number of projects in our sample 67% fall into this category. This is a standard practice in studies using this source of data and looking at local characteristics of aid projects (see e.g. Dreher et al., 2015; Briggs, 2018). Dropping projects in the pipeline and those with a precision code larger than 4 leaves us with a final sample of 878 observations (or project-locations).

In this final sample, Chinese assistance primarily consists of economic-oriented projects especially in Ethiopia, Nigeria and Uganda. Overall, transport, communication and energy projects account for 44% of the total number of projects. Education and health projects make up a large share of Chinese assistance too, accounting for about 21.3% of all projects (Figure 2). This is true in particular for Ghana (education alone represents 26% of the projects), Guinea and Malawi.

Figure 2. Distribution of Chinese aid projects by Sector



Source: Authors' elaboration based on Aid Data

[8] For more details see Aid Data's methodological notes: http://china.aiddata.org/content/methodology

Most of the projects (53.2%) included in our final sample are categorised as ODA-like; 41.8% are classified as Vague Official Finance, since information required for a more specific categorisation is lacking. Only 4.3% of all projects are classified as other official flows (OOF), which means commercial activities (mostly related to the communication sector, and including loans to build telecom infrastructures). Moreover, above 46% of project financing is provided in the form of loans, which seem to be China's preferred mode of foreign assistance.[9]

A few additional characteristics and limitations of the AidData dataset are important to keep in mind for the interpretation of our results (Strange et al. 2013). First, since China does not officially report data on its foreign assistance, project-related data is compiled from various sources, including governments, media, and the private sector. Therefore, the data might be not fully representative of Chinese assistance provided to sub-Saharan African countries. Second, a bias in China publicly reporting certain projects (but not others) cannot be ruled out (Strange et al. 2013). Third, since China's foreign assistance does not adhere to DAC standards and definitions, it is difficult to categorise it in the same way and with the same precision as aid from DAC donors. This reduces the comparability between aid flows from China and DAC member countries. Finally, and importantly, information on financial disbursements to projects is not available at the location level (i.e. the geographic project site level). Financial disbursement data is only available at the overall project level. In light of this, we do not use information on projects' financial flows in the main analysis. Instead, we indicate the presence of a project (location) in any given area with dummy variables. However, in order to take the intensity of treatment into account we repeat our main analysis by replacing the project location dummies with (a) the number of projects going to certain areas and (b) the actual financial size of the project (see Tables A10 and A11). As financial disbursement information is not available at the local level, we adopt the approach of other studies in the field and divide the total financial disbursement to a project by the number of its locations (see e.g. Dreher et al. 2016).

[9] http://www.sais-cari.org/publications-1/2017/7/5/policy-brief-112016-how-chinese-money-is-transforming-africa-its-not-what-you-think

2.2 Demographic and Health Survey (DHS)

The DHS is a large-scale survey programme. Data are nationally representative and include information for a wide range of indicators on several dimensions of households' wellbeing, including assets, education, health, and nutrition. All DHS surveys are based on a common questionnaire. This key feature allows us to analyse and compare the effect of Chinese aid on household welfare across countries. For the present analysis, we use DHS survey data on 13 African countries. We consider two data points for each country: a "pre-treatment" or "baseline" wave, close to the first year of the AidData dataset (2000) and a period characterised by little or no Chinese aid activities, and a "post-treatment" wave, which is the most recent DHS survey year. Countries and corresponding survey years are listed in Table A1 in the Appendix. Taken together, the surveys include information on 430,308 households.

In order to measure the impact of Chinese assistance on household welfare we consider a number of economic and social indicators. Concerning economic indicators, we use the wealth index that is directly available from the DHS as a measure of households' material well-being (Filmer and Pritchett, 1999, 2001; McKenzie, 2005). The DHS wealth index is generated by means of factor analysis and is based on assets such as a radio, refrigerator, telephone, television, the quality of the dwelling, water supply, access to sanitation facilities, and the type of flooring (Filmer and Pritchett, 1999, 2001; McKenzie, 2005). In all our analyses, we use the DHS wealth index, which ranks households on a continuous scale. The continuous scale is re-adjusted by adding a constant such that it contains only positive values; then it is transformed into its natural logarithm. Moreover, we use the wealth index recoded into national quintiles, also readily available from the DHS. It should be noted that the wealth index represents a relative measure of wealth within a specific country at a given point in time. Therefore, the index may not properly capture changes in households' wealth over time. Moreover, since assets can be country specific, the comparability of the index across countries may be limited.

In order to assess the impact of Chinese aid on local educational outcomes and, hence, households' human capital, we rely on two indicators: (a) the average and maximum years of education in each household (counting only members over 25 years of age) and (b) the educational attainment in each household. Educational attainment consists of six categories that are coded as follows: (0) "none", (1) "incomplete primary", (2) "complete primary", (3) "incomplete secondary", (4) "complete secondary", and (5) “higher education”. We consider the average and maximum value of educational attainment within each household for household members over 25 years of age. Summary statistics of all variables used in the analysis are provided in Table 1 (see Section 2.3).

2.3 Methodology

In order to link the DHS data to the information in Aid Data, we use geo-referred spatial information. The clusters surveyed in the DHS as well as the projects listed in Aid Data have point coordinates (GPS). We use these GPS coordinates to match household data from the DHS to sub-national project data from the Aid Data set.

The Aid Data information tells us when and where a Chinese aid project has been established. The DHS data tells us which household is located in an area close to such an aid project. Combining this information allows us to compare the welfare of households (with regard to wealth and education) before and after the implementation of a project.

We exploit the establishment of the Forum on China-Africa Cooperation (FOCAC) in 2000 as a possible source of exogenous variation in the provision of Chinese aid. According to existing analyses, anecdotal evidence and a few official sources such as the Ministry of Commerce (MOFCOM) and the White Papers on Foreign Aid, most of Chinese aid and other forms of economic cooperation have been flooding into Africa after the start of the new millennium and following pledges made during the FOCAC (triannual) meetings (Lum et al., 2009; Brautigam, 2009).[10] Evidence on the provision of Chinese loans (a major component of China’s overall aid flows) to Africa reported in Figure A1 in the Appendix is consistent with this hypothesis: for the continent as a whole Chinese flows in 2000 were nearly zero and then increased significantly afterwards.

[10] Malawi represents an exception since it was not affected by the first FOCAC, as it has established diplomatic relations with China only in 2008. In this specific case, we can compare HH’s living conditions in 2004 (a few years before relations with China normalised) with those in 2010 (i.e. a few years after).

Our empirical analysis leans on the methodology used by Kotsadam et al. (2018)[11] to evaluate the effectiveness of local aid projects on infant mortality at the household level by means of a difference-in-differences (DiD) approach. In our case, we have:

$$Y_{hcit} = \beta_0 + \beta_1 T_t + \beta_2 D_{hci} + \beta_3 (T_t * D_{hci}) + \beta_4 Z_{hcit} + \delta_x + \theta_{jt} + \varepsilon \qquad (1)$$

Where Y_{hcit} represents the outcome of interest (see Section 3.2) computed at the level of each household *h* based in a geographic cluster *c* in country *i* at time *t*. D is a dummy variable identifying the treatment group (=1). Households within a 25-kilometer (km) radius of a Chinese aid project are assigned to the treatment group, while households outside that radius are assigned to the control group. T is a dummy variable assuming the value of one if the information refers to the most recent DHS survey wave. Z_{hcit} is a vector of time variant characteristics measured at the household level. These characteristics include (a) the demographic composition of the households - number of persons living in the household, number of men, household members' average age, the dependency ratio, and a dummy variable (=1) if the household head is female; (b) the assets owned by the household (i.e. bike, car, radio and telephone), plus further proxy variables for living conditions such as access to electricity and flooring in the house; and (c) a dummy variable (=1) for households living in rural areas. Due to endogeneity, we include the variables measuring individual assets or proxying for living conditions only for the specification using educational outcomes as dependent variable (i.e. column 3 and following in each table), but not for the regressions using wealth as dependent variable. Furthermore, we add time varying country (θ_{jt}) and area (δ_x) fixed effects to control for time trends and area-specific characteristics that may be spuriously correlated with our dependent and independent variables.

Our approach to analysis (DiD) grounds on the premise that both DHS waves (before and after treatment with a Chinese aid project) are based on the same underlying population. However, since the DHS is not a panel, different survey waves are based on different sets of clusters and households within clusters. The chance that the same households are interviewed in both survey waves is extremely low. In order to deal with these limitations which can potentially bias our results we propose an alternative methodology to exploit our geo-referred data. This is done in three steps.

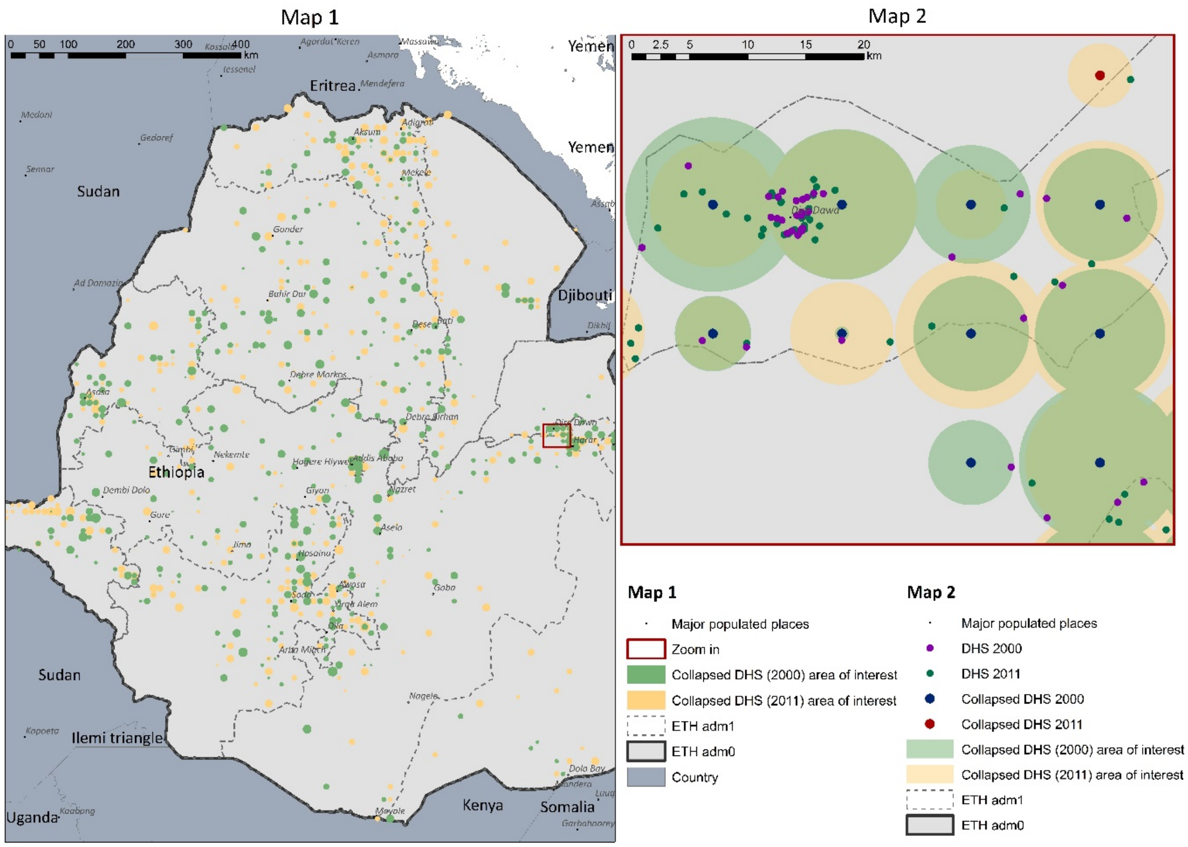
[11] See also earlier work by Kotsadam and Tolonen (2016), Isaksson and Kostadam (2018), and Wegenast et al. (2016).

First, we exploit the geographic proximity of clusters located in populated areas of the countries in our sample, taking our analysis from the household level to a more aggregated geographic-area level. Geographic areas are defined to share the first decimal place both for latitude and longitude coordinates which roughly corresponds to 8 km. Using the first decimal represents a good strategy to balance the number of clusters and the degree of homogeneity of the households included in each area. For each survey wave, we identify the clusters located within this geographic boundary. With this strategy, we can match the same areas in two different periods. Figure 3 provides a graphical representation of this procedure, using the Ethiopian data as an example. Map 1 reports the geographic distribution of the constructed areas in both survey waves. The dots represent our new, more aggregate, unit of analysis. Figure 3 shows the steps through which we move from clusters to aggregate areas in more detail. Purple dots are the original clusters in the 2000 wave, whereas the blue dot is the centroid of each newly constructed area. For areas around the blue dots we report collapsed information, summarising the data of all original clusters in 2000 that are located in the newly constructed area. This means that we compute the average characteristics of the households that have been surveyed. The aggregated areas in 2000 are then matched with the corresponding areas in 2011, which are constructed with the exact same methodology.[12] For Ethiopia, we have 84 geographic area units for which we can match information from pre-treatment surveys to post-treatment surveys (these are the overlapping green and yellow bubbles in Map 2, Figure 3). In total, our final sample includes 1229 geographic units that we observe over two periods.[13]

[12] Wegenast et al. (2016) propose a similar method since they re-aggregate information from the clusters to the district level, computing mean values to get to a dataset that varies by district and year. They do not, however, provide the additional steps we make in our analysis to ensure a more precise comparability between treated and control areas.

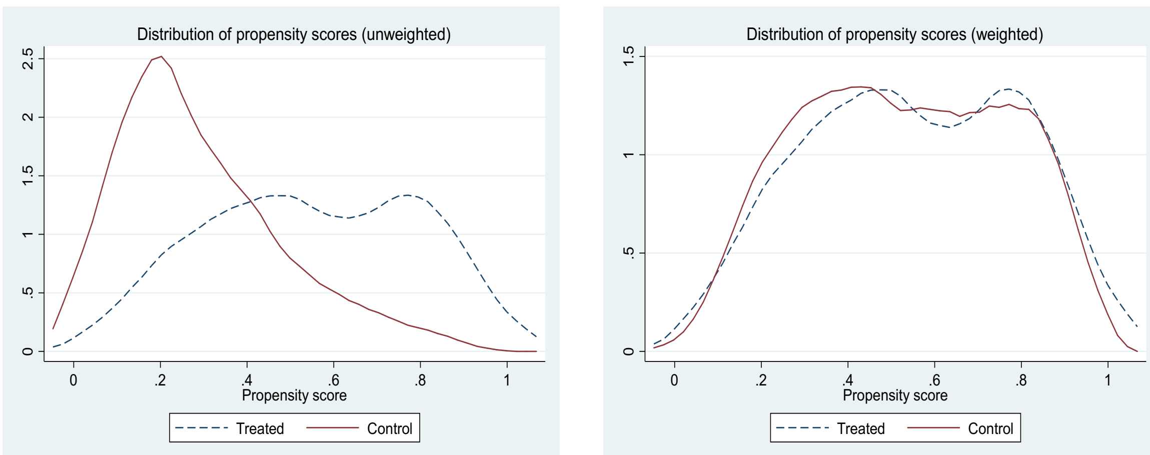
[13] Benin: 79 units; Cote d'Ivoire: 38; Ethiopia: 84; Ghana: 105; Guinea: 61; Kenya: 191; Malawi: 232; Nigeria: 96; Namibia; 87; Senegal: 61; Togo: 90; Uganda: 61; Zimbabwe: 44.

Figure 3. Procedures to construct areas



Second, we use a non–experimental technique called inverse probability weighting (IPW) to adjust for the selection bias that may results from the fact that we are dealing with non-randomised, observational data (Horvitz and Thompson 1952, Fitzgerald et al., 1988, Wooldridge, 2007). IWP aims at constructing a credible counterfactual from the data in two stages by identifying and then matching "quasi – identical" units in the treatment and control groups. For each area we use a probit model to estimate the probability of being a recipient of Chinese aid. Variables in the model includes the demographic composition of the households living in our unit of analysis (share of female-headed households, average age of household members, average size of households, share of men, share of children aged between 0 and 4, share of children aged between 5 and 14, share of children aged between 15 and 17, average dependency ratio), the assets owned by the same group of households (percentage of households holding a bike, a car and a radio) and other information to proxy living conditions (e.g. access to electricity and floor living conditions), the share of households living in rural areas as well as region fixed effects and year dummies. All variables are measured in the baseline year in order to reproduce initial conditions, and are computed as average levels among all households belonging to the same area. The graph depicting the weighted propensity scores for control and treatment groups indicates the goodness of the overall balance after matching (Figure 4, left panel). This is confirmed by the Hotelling test: after matching, we do not observe a significant difference in means between control and treatment group for the variables that were used to calculate the propensity scores (Prob > F (78,837) = 0.6335).

Figure 4. Distribution of propensity scores, before (left panel) and after (right panel) matching



Third, in our difference-in-difference analysis we weigh the control sample by the inverse of the probability computed in the previous stage in order to make it as comparable as possible to the treatment sample. The DiD specification now is:

$$Y_{xit} = \beta_0 + \beta_1 T_t + \beta_2 D_{xi} + \beta_3 (T_t * D_{xi}) + \beta_4 Z_{xit} + \delta_x + \theta_{jt} + \varepsilon \qquad (2)$$

The only difference with equation (1) is that *Y* and *Z* are now computed at the area-level *x* rather than at the household-level *h*. Standard errors are clustered at the area-level.

As outlined by Benyishay et al. (2017), following this approach allows one to control for confounding factors and omitted variables at a disaggregated geographic level. Additionally, time variant country fixed effects[14] account for factors potentially affecting the treatment and outcome variables at the national level and over time.[15] Table 1 reports descriptive statistics on the main variables used in the regression analysis.

Table 1: Descriptive Statistics

Variables	**Obs**	**Mean**	**Std. Dev.**	**Min**	**Max**
Dependent Variables					
Natural Logarithm (DHS Wealth Index)	1,748	13.94	0.45	-2.30	15.03
DHS Wealth Index Quintiles	1,748	3.18	1.01	1.00	5.00
Average Years of Education	2,219	5.41	3.12	0.00	15.60
Max. Years of Education	2,219	6.82	3.33	0.00	16.92
Average Educational Attainment	2,219	1.63	0.97	0.00	4.72
Max. Educational Attainment	2,219	2.07	1.05	0.00	5.00
Treatment Variables					
Treated (D) with Project	2,458	0.35			
Number of Projects	2,458	6.22	46.28	0.00	1234
Total Amount (Financial Volume)	2,458	79.67	831.09	0.00	35048
Household Characteristics					
Female-Headed Household	2,280	0.26	0.16	0.00	1.00
Age of Household Members	2,280	43.86	6.10	26.95	72.59
Household Size	2,280	6.23	2.41	2.10	28.83
No. of Men in Household	2,458	0.45	0.30	0.00	2.24
Dependency Ratio	2,280	0.50	0.09	0.26	0.87
Access to Electricity	2,280	0.33	0.38	0.00	1.00
Household Assets					
Radio	2,280	0.65	0.22	0.00	1.00
Bicycle	2,280	0.30	0.24	0.00	1.00
Car	2,280	0.08	0.13	0.00	0.88
Telephone	2,129	0.05	0.12	0.00	0.94
Type of Flooring	2,280	2.06	0.75	1.00	3.00
Rural Area	2,280	0.65	0.45	0.00	1.00

Source: Authors' elaboration on DHS data

Note: All the variables are calculated at the area-level. See Section 3 for the construction of how geographic areas have been constructed.

[14] Note that adding fixed effects to our model causes the treatment dummy *D* to being dropped from the regression due to perfect collinearity.

[15] We do not include region-year specific effects (as for instance done by Isaksonn and Kostadam, 2018) since the areas we constructed might include clusters belonging to different regions (although this happens in a minority of cases). The fixed effects at the level of constructed areas that are absorbed by the DiD represent a higher level compared to the regions.

3. Main Results

Our main analysis is reported in Table 2. The results indicate that Chinese Aid projects have a positive and significant effect on the wellbeing of households in the sub-Saharan countries forming part of our sample.

Concerning households' material well-being, we observe that areas located in the proximity of a Chinese project site seem to be wealthier than "control" areas located farther away from such project sites. This result holds for both the continuous wealth index taken from the DHS survey (Table 2, column 1) and the index reflecting the wealth distribution across quintiles (Table 2, column 2). Thus, apparently, treated areas are relatively wealthier than control areas; and they are more likely to be in a higher wealth quintile. To some extent, these findings fit with the results by Dreher et al. (2016) who identify a positive effect of Chinese aid at the regional level in Africa. However, our results do generally not imply a causal relationship between Chinese projects and household wealth: for the majority of our sample countries, wealth indicators are only available in the latest DHS survey waves (post-treatment). Consequently, we cannot compare control and treatment areas over time and our DiD model (subsection 2.3, equation (2)) reduces to a cross-section which does not allow for a causal interpretation of the data. Except for the analysis presented in Table A2 in Appendix I, this situation applies to all wealth-related regressions in this study. Importantly, while the previous results seem to confirm a wealth enhancing effect of Chinese development assistance, the analysis of the distribution of such benefits across quantiles of the wealth index says little about redistributive effects. For example, Chinese aid could have an equalising effect if it moved areas in lower quintiles up into higher quintiles. The opposite would apply if it mostly benefitted areas that were already in higher quintiles before receiving a project. A deeper examination of distributional effects of Chinese aid at the sub-national and micro-level certainly deserves more attention.

The analysis on education outcomes (Table 2, columns 3 to 6) is based on our full DiD specification, since data is available for both survey waves.[16] This being said, the results presented in columns 3 to 6 indicate that Chinese aid projects have a positive and significant effect (a) on average and maximum

[16] As discussed in subsection 2.3, adding fixed effects to our model causes the treatment dummy *D* to being dropped from the regression due to perfect collinearity. This automatism does not affect the interpretation of the DiD estimator, which is our main variable of interest, but we lose information on differences between control and treatment areas at baseline. That means, the regression results do not reveal whether Chinese aid projects went to areas with initially higher or lower education levels.

years of education, and (b) on average and maximum educational attainment (the level of acquired education). The positive and significant post-treatment dummy *T* indicates that educational outcomes have generally improved over time in sub-Saharan Africa. This is well in line with other studies and a well-known fact by now (Riddel and Niño-Zarazúa, 2016). Several mechanisms may explain these results. First, better educational outcomes can be a direct result of (successful) Chinese projects in the education sector. After all, education-related projects account for 11% of the total sectoral distribution of Chinese aid (see Figure 2). In Section 4 we study this possible mechanism more closely. Second, better educational outcomes can be an indirect result of projects with relevant spillover effects. Infrastructural projects for instance, which make up at least 21% of Chinese aid, can facilitate access to education for a large number of pupils. Third, increased economic wellbeing, possibly driven by Chinese aid projects, may also contribute to improved educational outcomes in treatment areas, for example by enabling households to pay for education.

Finally, most of the control variables added to each regression play the expected role on the different outcomes examined.

Table 2: Main Results, OLS Weighted (IWP)

	(1)	(2)	(3)	(4)	(5)	(6)
	Ln (DHS Wealth Index)	DHS Wealth Index Quintiles	Average Years of Education	Average Educational Attainment	Max. Years of Education	Max. Educational Attainment
Treated (*D*) with Project	0.025***	0.139***	automatically dropped			
	[0.009]	[0.053]				
Treated*Survey Year (*D*T*)			0.510***	0.167***	0.466***	0.162***
			[0.157]	[0.052]	[0.169]	[0.058]
Most Recent Survey Year (*T*)			2.150***	0.310***	2.018***	0.192**
			[0.295]	[0.093]	[0.295]	[0.097]
Female-Headed HH[1]	0.067	0.880***	0.376	0.020	0.379	0.008
	[0.045]	[0.230]	[0.461]	[0.155]	[0.491]	[0.177]
Age Of HH members	0.001	0.016***	-0.075***	-0.024***	-0.044**	-0.014**
	[0.001]	[0.006]	[0.019]	[0.006]	[0.020]	[0.006]
HH Size	0.003	-0.069**	0.094	0.032	0.320***	0.106***
	[0.009]	[0.028]	[0.081]	[0.027]	[0.084]	[0.029]
No. Of Men in HH	0.013	0.234*	-0.549**	-0.176**	-0.419	-0.148
	[0.040]	[0.140]	[0.261]	[0.089]	[0.262]	[0.099]
Rural Area	-0.111***	-1.120***	-0.584**	-0.203***	-0.816***	-0.276***
	[0.017]	[0.109]	[0.234]	[0.077]	[0.281]	[0.090]
Dependency Ratio	0.463***	4.116***	2.443**	0.837**	3.320***	1.042***
	[0.119]	[0.603]	[1.075]	[0.337]	[1.171]	[0.364]
Access To Electricity			0.828**	0.264**	0.816*	0.201
			[0.388]	[0.127]	[0.421]	[0.140]
Radio			2.720***	0.804***	2.744***	0.819***
			[0.440]	[0.142]	[0.470]	[0.157]
Bicycle			0.172	-0.003	0.651	0.126
			[0.394]	[0.131]	[0.435]	[0.145]
Car			3.844***	1.287***	3.587***	1.248***
			[0.897]	[0.283]	[0.857]	[0.275]
Type Of Flooring			0.744***	0.322***	0.948***	0.430***
			[0.166]	[0.065]	[0.180]	[0.073]
Telephone			1.063	0.313	0.953	0.311
			[0.699]	[0.240]	[0.672]	[0.237]
Country-Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Constant	13.714***	1.420***	2.237*	0.808**	0.229	0.191
	[0.093]	[0.533]	[1.166]	[0.386]	[1.303]	[0.433]
Obs. = No. Of Areas	968	968	1,767	1,767	1,767	1,767
R-squared	0.419	0.735	0.620	0.613	0.584	0.580
Number Of Areas			968	968	968	968

Robust standard errors clustered at the area-level, *** p<0.01, ** p<0.05, * p<0.1; [1]HH: Household

Note: All the variables are calculated at the area-level. See Section 3 for the construction of how geographic areas have been constructed.

3.1 Robustness of Main Results

In order to test the robustness of our main results, we apply the following changes to the data. First, we include wealth indicators at baseline for countries for which this information is available across both survey waves. The use of baseline information allows us to run DiD regressions and address the aforementioned concerns related to cross-sectional models. Second, we exclude potential outliers: areas that received a large number of projects. Third, we test how sensitive results are to enlarging the buffer zone (50 km) that is used to assign areas to treatment and control groups.

(i) Including wealth-related information at baseline

For Kenya, Malawi and Nigeria, comparable wealth-related data is available across both survey waves. The DiD regressions reported in Table A2 (Appendix I) are based on the sample of these three countries. The results are very consistent with the results of the cross-sectional analysis reported in Table 2 above. The DiD coefficients indicate that Chinese projects have a positive and significant effect on the wealth of households located in their vicinity. Moreover, the post-treatment dummy (*T*) indicates that household wealth has generally not increased over time in the sampled countries. That means, while wealth did not increase in Kenya, Malawi and Nigeria over time and overall, areas treated with Chinese aid nevertheless experienced a significant increase in wealth.

(ii) Excluding potential outliers

The distribution of projects across areas shows that the 25th percentile benefitted from only 2 projects while the 90th and 95th percentile from 75 projects and 181 projects, respectively (Figure A2, Appendix III). Therefore, we test to what degree our results may be driven by areas recording a large number of projects. First, we exclude areas recording more than 75 projects (left panel of Table A3, Appendix I). Then, we exclude areas recording more than 181 projects (right panel of Table A3, Appendix I). Our results remain robust to the exclusion of these outlier areas.

(iii) Adopting a larger buffer zone

Finally, we test to what extent choosing a larger buffer zone of 50km (in order to assign areas to control and treatment groups) affects our main findings. Results are presented in Table A4 in Appendix I. We observe that Chinese aid projects still have a positive and significant impact on the wealth of households (areas) that live up to 50km away from the project site. However, the effect such projects on educational outcomes apparently wears off with increasing distance. This seems reasonable: education-related interventions are likely local in nature (such as the construction of schools or provision of other services), reaching a limited amount of people. This, in turn, may limit spillover effects beyond a certain geographical distance.

4. Sectoral Analysis of Chinese Aid

In this section, we discuss the results of our sectoral analysis of Chinese aid. The sectoral analysis serves two main purposes. First, it allows us to take the heterogeneity of aid projects and their potentially heterogeneous effects on household well-being into account. Second, it allows us to more directly link projects to their intended outcomes: we can link education projects to education outcomes (columns 3 to 6, Table A7, Appendix II) and economic projects to economic outcomes (columns 1 and 2, Table A5, Appendix II). We group all projects into two big categories on the basis of their Creditor Report System (CRS) sectoral codes: social sector projects and economic sector projects.[17] Regression results are presented in Tables A5 to A7 in Appendix II.

Table A5 shows the effect of economic projects on our outcome variables (education and material well-being). We find that economic sector projects have a positive and significant effect on both educational outcomes and wealth. Thus, it seems that projects in the economic sector directly affect households' material well-being (wealth) and have positive second-order effects in the realm of education.

Tables A6 and A7 show the effect of social sector and education projects on households' well-being. The data suggest that benefits generated by social sector projects in general and education projects in particular are not as broad as benefits generated by economic projects, since the effect of education on wealth (see column 1, Tables A6 and A7) is not significant anymore. However, social sector and

[17] Economic projects include: Transport and Storage (210); Communications (220); Energy Generation and Supply (230); Banking and Financial Services (240); Business and Other Services (250); Agriculture, Forestry and Fishing (310); Industry, Mining, Construction (320); Trade and Tourism (330). Social projects include: Education (110); Health (120); Population Policies (130); Water Supply and Sanitation (140); Government and Civil Society (150); Other Social Infrastructure and Services (160); Women in Development (420); Developmental Food Aid (520); Non-Food Commodity Assistance (530). CRS codes are provided in parentheses.

education projects still have a positive and significant effect on households' likelihood of belonging to a higher wealth quintile. To some extent, this fits the results of studies showing that education interventions can result in significant monetary returns to individuals, for example due to better labour market outcomes (see Heynemann and Lee, 2017).

The results in columns 3 to 6 show that education projects have a significant and positive effect on all educational outcomes we consider, suggesting that Chinese aid does improve well-being in this important area. The finding is consistent with macro-level studies that find a positive relationship between education aid provided by Western donors and educational outcomes in developing countries (see e.g. Michaelowa and Weber, 2007, Birchler and Michaelowa, 2016 as well as Heynemann and Lee, 2017 and Riddel and Niño-Zarazúa, 2016 for a review of findings on the effectiveness of education aid.) Furthermore, it is consistent with micro- and project-level studies which also find a positive relationship between education interventions and outcomes (see Heynemann and Lee, 2017 and Riddel and Niño-Zarazúa, 2016).

Overall, our findings provide new evidence on the role of China as a provider of education aid, underlining the government's strong emphasis on human resource development especially in Sub Saharan Africa (King, 2014). Furthermore, similar to the aid effectiveness literature that focusses on heterogeneous effects of different types of aid (in terms of sector, form of delivery, location, or distance to beneficiaries) (Clemens et al., 2012, Briggs, 2018), our results indicate that different types of Chinese aid too have heterogeneous effects on the outcome variables we consider.

5. Distribution and Scale of Chinese Aid

In our main analysis, we focus on whether a project is implemented or not and refrain from using potentially less reliable information on the number of projects or project volumes. An obvious limitation of this approach is that it does not consider the scale of projects and, hence, the intensity of treatment on treated areas. Therefore, we may be underestimating the overall effects of Chinese project assistance on household well-being. Moreover, our approach does not allow us to test for non-linear effects of aid that have been identified by earlier macro- and project-level studies. We adjust our main specification as described below, such that we can explore these additional aspects with regard to Chinese assistance.

As laid out in Section 2.1, we take the intervention scale into account by replacing project location dummies - indicating the presence of a project (yes or no) - with (a) the number of projects going to certain areas (see Table A9, Appendix III), and (b) the actual financial volume of the project (see Table A10, Appendix III). Moreover, we apply an extension to our analysis by using the *propensity score-based marginal mean weighting through stratification* (MMWS) method (Hong, 2010; Hong, 2012; Huang et al 2005). MMWS combines *propensity score stratification* and *inverse probability of treatment weighting* in order to reduce selection bias and is applicable to estimating causal effects of so-called multivalued treatments which can take on more than one value (Linden et al. 2014). Based on the distribution of the number of projects (Table A8, Appendix III) we consider three, hence multivalued, ordinal treatment levels: one single project (25^{th} percentile), more than one project but less than 17 projects (25^{th} to 75^{th} percentile), and 17 or more projects (>75^{th} percentile). Based on the distribution of financial project size, we consider the following three treatment levels: higher than zero but lower than 37.71 $ million (25^{th} percentile); equal or more than 37.71 $ million but lower than 252.98 $ million (25^{th} to 75^{th} percentile); equal or higher than 252.98 $ million (95^{th} percentile). As before, areas not located within a 25km radius of a Chinese aid project serve as the control group.

Now, MMWS serves to reduce selection bias by achieving balance on baseline (and observable) characteristics between all treatment levels (Linden et al. 2014). The empirical strategy relies on four steps. First, we compute the generalised propensity score for each area. To this end, we use an ordered logistic regression and regress our ordinal treatment variable on the relevant set of covariates. Second, the generalised propensity scores that we computed for each area is stratified into four strata. Third, we compute the MMWS weights for each area corresponding to its stratum and treatment level. Finally, we re-estimate our main specifications using the MMWS as probability weights.

The results presented in Table A9 indicate that the treatment intensity in terms of the number of projects matters: the effect on our outcome variables is non-linear. More specifically, Chinese aid projects do not seem to have a significant impact on areas recording only one project. Instead, depending on the outcome variable we consider, the impact is positive in areas counting more than one and up to 17 projects (e.g. wealth), or in areas counting more than 17 projects (e.g. wealth quintiles). In other words, the threshold at which Chinese projects affect household welfare varies with the outcome variable.

Table A10 reports the regressions that include treatment intensity based on financial project volume. The results point in a similar direction as the results in Table A9: the impact of Chinese assistance is only statistically significant after a certain threshold has been reached. We observe again that the threshold at which Chinese assistance becomes effective apparently depends on the type of outcome variable (compare columns 1 and 2 in Table A10). With respect to education outcomes we moreover observe that project effects only turn significant at the highest treatment level (see columns 3 to 6 in Table A10). This suggests that improvements of educational outcomes only kick in once a comparatively larger amount of financial resources have been spent on a project.

In summary, the results in Tables A9 and A10 are an important addition to our work. On the one hand, they support our core results by pointing to a positive relation between Chinese aid and household welfare that is robust to a treatment indicator that accounts for the scale of the projects. On the other hand, we believe they complement our analysis in two main respects: First, the relationship between treatment level and outcome variables is non-linear. Second, the threshold at which Chinese assistance becomes effective varies with the outcome variables on the one hand (wealth, wealth quintiles, education outcomes) and the treatment variable on the other hand (number of projects and project volume).

6. Discussion

China is rapidly becoming an important source of development assistance to low-income countries, especially in sub-Saharan Africa. While the lack of reliable statistics on Chinese aid has thus far limited the analysis of its effectiveness, recent work seems to point to positive effects on national and sub-national economic growth – e.g. Dreher et al. (2016) and Dreher et al. (2017). In this paper, we go a step further and evaluate the effectiveness of Chinese aid on the welfare of households based in 13 SSA countries. Our empirical strategy grounds on a novel methodology which relies on quasi-experimental and impact evaluation methods to reduce the potential bias due to the lack of a perfect counterfactual. Combining a rich set of georeferenced data on Chinese foreign assistance projects with household-level information from the DHS, we provide first evidence of a positive effect of Chinese projects on the wellbeing of households located in our sample countries. Areas that receive such projects are more likely to be wealthier, and they are more likely to be in a higher wealth quintile. Moreover, households located in areas that receive such projects stay in school longer, and achieve a higher educational attainment than areas which did not receive such projects. Results also show that aid sectoral composition matters, and that accounting for the size of aid has a non-linear relation with some of the outcomes.

The present paper is a first step towards analysing the effectiveness of Chinese foreign assistance on the household level. In future research, we plan to investigate further topics which are immediately related to this paper. First, household welfare should be more comprehensively assessed by including further dimensions of well-being such as for example consumption. Consumption was not included in the present analysis due a lack of corresponding information in the DHS. Second, we plan to address some of the shortcomings related to measuring wealth and its distribution with DHS data, with the goal to provide insights on the relationship between aid and inequality. While our main results seem to confirm a wealth enhancing effect of Chinese aid, the analysis of the distribution of such benefits says little about redistributive effects. Third, we are interested on measuring the impact of Chinese development assistance on labour market outcomes. Finally, we plan to replicate our methodology in order to assess the effectiveness of other donors' foreign assistance (for which georeferenced information exists) and compare it to Chinese assistance.

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Appendix

I. DHS Data and Robustness Of Main Results

Table A1: DHS Data Availability		
Country	**Baseline**	**After Treatment**
Benin	1996	2012
C. d'Ivoire	1999	2012
Ethiopia	2000	2010
Ghana	1998	2014
Guinea	1999	2012
Kenya	2003	2014
Malawi	2004	2015
Namibia	2000	2013
Nigeria	2003	2013
Senegal	1997	2012
Togo	1998	2013
Uganda	2001	2006
Zimbabwe	1999	2015

Table A2: Robustness Test Main Results, OLS weighted (IWP) – Considering Wealth Index at Baseline (Kenya, Malawi, Nigeria only)

	(1)	(2)
	Ln (DHS Wealth Index)	DHS Wealth Index Quintiles
Treated (*D*) with Project	automatically dropped	
Treated*Survey Year (*D*T*)	0.017***	0.303***
	[0.005]	[0.092]
Most Recent Survey Year (*T*)	-0.014*	-0.170
	[0.008]	[0.119]
Female-Headed HH[1]	0.017	0.051
	[0.018]	[0.312]
Age Of HH members	-0.000	0.001
	[0.001]	[0.008]
HH Size	0.003	0.005
	[0.004]	[0.051]
No. Of Men in HH	-0.001	0.074
	[0.009]	[0.152]
Rural Area	-0.050***	-0.807***
	[0.009]	[0.161]
Dependency Ratio	0.236***	3.631***
	[0.040]	[0.526]
Country-Year FE	Yes	Yes
Constant	13.856***	1.985***
	[0.035]	[0.514]
Obs. = No. Of Areas	966	966
R-squared	0.515	0.444
Number Of Areas	483	483

Robust standard errors clustered at the area-level, *** p<0.01, ** p<0.05, * p<0.1
[1]HH: Household
Note: All the variables are calculated at the area-level. See Section 3 for the construction of how geographic areas have been constructed.

Table A3: Robustness Test Main Results, OLS weighted (IWP) – Excluding Outliers (No. of Projects)

	Excluding areas with more than 75 projects (90th percentile)						Excluding areas with more than 181 (95th percentile)					
	Ln (DHS Wealth Index)	DHS Wealth Index Quintiles	Average Years of Education	Average Educational Attainment	Max. Years of Education	Max. Educational Attainment	Ln (DHS Wealth Index)	DHS Wealth Index Quintiles	Average Years of Education	Average Educational Attainment	Max. Years of Education	Max. Educational Attainment
Treated (*D*) with Project	0.024**	0.118**	automatically dropped				0.026***	0.128**	automatically dropped			
	[0.009]	[0.053]					[0.009]	[0.053]				
Treated*Survey Year (*D*T*)			0.481***	0.156***	0.450***	0.155***			0.518***	0.169***	0.481***	0.166***
			[0.155]	[0.052]	[0.166]	[0.057]			[0.155]	[0.052]	[0.166]	[0.057]
Most Recent Survey Year (*T*)			1.993***	0.278***	1.746***	0.122			2.143***	0.313***	1.992***	0.195*
			[0.325]	[0.101]	[0.312]	[0.101]			[0.302]	[0.095]	[0.300]	[0.099]
Female-Headed HH[1]	0.071	0.907***	0.379	0.023	0.434	0.034	0.066	0.889***	0.373	0.014	0.379	0.007
	[0.046]	[0.228]	[0.460]	[0.154]	[0.495]	[0.178]	[0.046]	[0.229]	[0.460]	[0.155]	[0.492]	[0.178]
Age Of HH members	0.001	0.016**	-0.075***	-0.023***	-0.044**	-0.014**	0.001	0.016**	-0.076***	-0.024***	-0.044**	-0.014**
	[0.001]	[0.006]	[0.019]	[0.006]	[0.020]	[0.007]	[0.001]	[0.006]	[0.019]	[0.006]	[0.020]	[0.006]
HH Size	0.003	-0.074***	0.069	0.023	0.290***	0.096***	0.004	-0.069**	0.086	0.030	0.311***	0.104***
	[0.009]	[0.029]	[0.081]	[0.026]	[0.084]	[0.029]	[0.009]	[0.028]	[0.080]	[0.026]	[0.083]	[0.029]
No. Of Men in HH	0.011	0.266*	-0.443*	-0.124	-0.284	-0.087	0.012	0.248*	-0.538**	-0.167*	-0.412	-0.141
	[0.040]	[0.141]	[0.252]	[0.082]	[0.251]	[0.092]	[0.040]	[0.141]	[0.261]	[0.090]	[0.263]	[0.100]
Rural Area	-0.112***	-1.105***	-0.544**	-0.185**	-0.771***	-0.258***	-0.112***	-1.107***	-0.578**	-0.202***	-0.809***	-0.277***
	[0.017]	[0.109]	[0.242]	[0.078]	[0.292]	[0.092]	[0.017]	[0.109]	[0.238]	[0.078]	[0.285]	[0.091]
Dependency Ratio	0.491***	4.056***	2.199**	0.767**	3.110***	0.985***	0.482***	4.100***	2.311**	0.813**	3.208***	1.017***
	[0.125]	[0.617]	[1.096]	[0.343]	[1.196]	[0.372]	[0.124]	[0.612]	[1.088]	[0.341]	[1.187]	[0.370]
Access To Electricity			0.781**	0.255**	0.758*	0.183			0.777**	0.251**	0.767*	0.189
			[0.397]	[0.130]	[0.435]	[0.144]			[0.387]	[0.127]	[0.423]	[0.140]
Radio			2.746***	0.809***	2.779***	0.830***			2.699***	0.796***	2.710***	0.810***
			[0.443]	[0.144]	[0.477]	[0.159]			[0.441]	[0.143]	[0.473]	[0.158]
Bicycle			0.158	-0.007	0.626	0.121			0.167	-0.004	0.641	0.129
			[0.395]	[0.131]	[0.438]	[0.146]			[0.392]	[0.130]	[0.434]	[0.144]
Car			3.921***	1.316***	3.770***	1.295***			3.917***	1.306***	3.677***	1.251***
			[0.991]	[0.313]	[0.945]	[0.303]			[0.975]	[0.309]	[0.931]	[0.300]
Type Of Flooring			0.774***	0.332***	0.955***	0.435***			0.771***	0.330***	0.967***	0.438***
			[0.170]	[0.066]	[0.185]	[0.075]			[0.168]	[0.065]	[0.182]	[0.074]
Telephone			1.142	0.333	1.073	0.337			1.107	0.321	1.003	0.311
			[0.843]	[0.290]	[0.822]	[0.290]			[0.827]	[0.284]	[0.804]	[0.284]
Country-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Constant	13.705***	1.409**	2.501**	0.851**	0.671	0.294	13.707***	1.434***	2.334**	0.814**	0.368	0.208
	[0.096]	[0.546]	[1.191]	[0.395]	[1.335]	[0.445]	[0.096]	[0.541]	[1.185]	[0.394]	[1.324]	[0.441]
Obs = No. Of Areas	924	924	1,723	1,723	1,723	1,723	946	946	1,745	1,745	1,745	1,745
R-squared	0.380	0.719	0.623	0.622	0.585	0.587	0.413	0.725	0.623	0.617	0.586	0.582
Number Of Areas			959	959	959	959			964	964	964	964

Robust standard errors clustered at the area-level, *** p<0.01, ** p<0.05, * p<0.1; [1]HH: Household

Table A4: Robustness Test Main Results, OLS weighted (IWP) – Buffer Zone 50 km

	(1)	(2)	(3)	(4)	(5)	(6)
	Ln (DHS Wealth Index)	DHS Wealth Index Quintiles	Average Years of Education	Average Educational Attainment	Max. Years of Education	Max. Educational Attainment
Treated (*D*) with Project	0.064*	0.102*				
	[0.034]	[0.054]				
Treated*Survey Year (*D*T*)			0.066	0.041	-0.031	0.025
			[0.133]	[0.042]	[0.144]	[0.048]
Most Recent Survey Year (*T*)			2.283***	0.409***	2.302***	0.356***
			[0.289]	[0.092]	[0.316]	[0.105]
Female-Headed HH[1]	0.277	0.800***	0.898*	0.217	0.721	0.155
	[0.184]	[0.215]	[0.458]	[0.137]	[0.463]	[0.150]
Age Of HH members	0.002	0.018***	-0.062***	-0.021***	-0.021	-0.007
	[0.003]	[0.007]	[0.015]	[0.005]	[0.017]	[0.006]
HH Size	0.036	0.007	-0.016	-0.005	0.170**	0.055**
	[0.027]	[0.018]	[0.066]	[0.022]	[0.073]	[0.024]
No. Of Men in HH	0.042	0.189*	0.161	0.047	0.351	0.103
	[0.057]	[0.103]	[0.259]	[0.087]	[0.247]	[0.082]
Rural Area	-0.146***	-1.145***	-0.496**	-0.169***	-0.761***	-0.246***
	[0.024]	[0.096]	[0.206]	[0.063]	[0.249]	[0.080]
Dependency Ratio	0.922***	4.913***	2.229**	0.725**	2.788**	0.871**
	[0.354]	[0.512]	[1.020]	[0.321]	[1.154]	[0.376]
Access To Electricity			1.410***	0.462***	1.659***	0.507***
			[0.308]	[0.097]	[0.371]	[0.122]
Radio			1.784***	0.556***	1.890***	0.589***
			[0.431]	[0.133]	[0.529]	[0.173]
Bicycle			0.941**	0.236*	0.904**	0.196
			[0.377]	[0.121]	[0.428]	[0.143]
Car			3.808***	1.280***	3.536***	1.201***
			[0.764]	[0.237]	[0.815]	[0.261]
Type Of Flooring			0.660***	0.236***	0.781***	0.295***
			[0.170]	[0.054]	[0.191]	[0.063]
Telephone			1.824***	0.640***	1.726***	0.659***
			[0.539]	[0.183]	[0.481]	[0.159]
Country-Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Constant	13.186***	0.391	1.975*	0.817**	-0.001	0.214
	[0.483]	[0.481]	[1.108]	[0.346]	[1.224]	[0.394]
Obs = No. Of Areas	1,141	1,141	2,041	2,041	2,041	2,041
R-squared	0.095	0.687	0.609	0.601	0.567	0.548
Number Of Areas			1,141	1,141	1,141	1,141

Robust standard errors in brackets *** p<0.01, ** p<0.05, * p<0.1; [1]HH: Household

Note: All the variables are calculated at the area-level. See Section 3 for the construction of how geographic areas have been constructed.

II. Sectoral Analysis Of Chinese Assistance

Table A5: Robustness Test Main Results, OLS weighted (IWP) – Economic Projects

	(1)	(2)	(3)	(4)	(5)	(6)
	Ln (DHS Wealth Index)	DHS Wealth Index Quintiles	Average Years of Education	Average Educational Attainment	Max. Years of Education	Max. Education al Attainment
Treated (*D*) with Project	0.031***	0.144***				
	[0.010]	[0.055]				
Treated*Survey Year (*D*T*)			0.430***	0.135**	0.378**	0.113*
			[0.164]	[0.055]	[0.177]	[0.060]
Most Recent Survey Year (*T*)			2.244***	0.344***	2.112***	0.234**
			[0.293]	[0.093]	[0.289]	[0.096]
Female-Headed HH[1]	0.070	0.897***	0.392	0.025	0.393	0.011
	[0.045]	[0.232]	[0.465]	[0.156]	[0.495]	[0.178]
Age Of HH members	0.001	0.017***	-0.072***	-0.023***	-0.041**	-0.013*
	[0.001]	[0.006]	[0.019]	[0.006]	[0.020]	[0.006]
HH Size	0.003	-0.071**	0.076	0.026	0.304***	0.100***
	[0.009]	[0.028]	[0.081]	[0.027]	[0.084]	[0.029]
No. Of Men in HH	0.014	0.245*	-0.500*	-0.160*	-0.374	-0.132
	[0.040]	[0.140]	[0.259]	[0.089]	[0.260]	[0.099]
Rural Area	-0.111***	-1.122***	-0.602**	-0.210***	-0.833***	-0.283***
	[0.017]	[0.108]	[0.237]	[0.077]	[0.280]	[0.090]
Dependency Ratio	0.454***	4.080***	2.253**	0.775**	3.147***	0.983***
	[0.119]	[0.599]	[1.079]	[0.339]	[1.169]	[0.365]
Access To Electricity			0.842**	0.269**	0.831*	0.209
			[0.396]	[0.129]	[0.429]	[0.143]
Radio			2.729***	0.805***	2.748***	0.816***
			[0.444]	[0.143]	[0.472]	[0.158]
Bicycle			0.196	0.005	0.673	0.136
			[0.400]	[0.133]	[0.441]	[0.147]
Car			3.898***	1.306***	3.639***	1.268***
			[0.917]	[0.290]	[0.874]	[0.282]
Type Of Flooring			0.746***	0.322***	0.950***	0.432***
			[0.170]	[0.066]	[0.184]	[0.075]
Telephone			1.068	0.313	0.954	0.307
			[0.709]	[0.243]	[0.681]	[0.240]
Country-year FE	Yes	Yes	Yes	Yes	Yes	Yes
Constant	13.710***	1.422***	2.258*	0.815**	0.248	0.197
	[0.092]	[0.532]	[1.176]	[0.389]	[1.309]	[0.434]
Obs = No. Of Areas	968	968	1,767	1,767	1,767	1,767
R-squared	0.420	0.734	0.616	0.609	0.580	0.575
Number Of Areas			968	968	968	968

Robust standard errors in brackets *** p<0.01, ** p<0.05, * p<0.1; [1]HH: Household

Note: All the variables are calculated at the area-level. See Section 3 for the construction of how geographic areas have been constructed. Economic related projects include projects in the following Sectors (CRS code in parenthesis): Transport and Storage (210); Communications (220); Energy Generation and Supply (230); Banking and Financial Services (240); Business and Other Services (250); Agricolture, Forestry and Fishing (310); Industry, Mining, Constructurion (320); Trade and Tourism (330).

Table A6: Robustness Test Main Results, OLS weighted (IWP) – Social Sector Projects

	(1)	(2)	(3)	(4)	(5)	(6)
	Ln (DHS Wealth Index)	DHS Wealth Index Quintiles	Average Years of Education	Average Educational Attainment	Max. Years of Education	Max. Educational Attainment
Treated (*D*) with Project	0.014	0.174***				
	[0.009]	[0.053]				
Treated*Survey Year (*D*T*)			0.514***	0.157***	0.482***	0.154***
			[0.159]	[0.052]	[0.170]	[0.057]
Most Recent Survey Year (*T*)			2.317***	0.367***	2.168***	0.248***
			[0.286]	[0.090]	[0.280]	[0.092]
Female-Headed HH[1]	0.063	0.828***	0.320	0.002	0.328	-0.009
	[0.045]	[0.225]	[0.452]	[0.152]	[0.483]	[0.175]
Age Of HH members	0.001	0.016***	-0.073***	-0.023***	-0.042**	-0.013**
	[0.001]	[0.006]	[0.019]	[0.006]	[0.020]	[0.006]
HH Size	0.002	-0.074***	0.076	0.026	0.304***	0.100***
	[0.009]	[0.027]	[0.079]	[0.026]	[0.082]	[0.028]
No. Of Men in HH	0.016	0.238*	-0.549**	-0.175**	-0.420	-0.147
	[0.039]	[0.137]	[0.260]	[0.089]	[0.259]	[0.097]
Rural Area	-0.112***	-1.115***	-0.573**	-0.201***	-0.805***	-0.273***
	[0.017]	[0.109]	[0.236]	[0.077]	[0.281]	[0.090]
Dependency Ratio	0.456***	3.984***	2.450**	0.835**	3.330***	1.041***
	[0.119]	[0.597]	[1.065]	[0.333]	[1.159]	[0.360]
Access To Electricity			0.829**	0.265**	0.815*	0.203
			[0.389]	[0.128]	[0.424]	[0.142]
Radio			2.716***	0.800***	2.741***	0.816***
			[0.438]	[0.142]	[0.468]	[0.157]
Bicycle			0.146	-0.010	0.624	0.120
			[0.401]	[0.133]	[0.439]	[0.146]
Car			3.711***	1.249***	3.461***	1.210***
			[0.892]	[0.282]	[0.851]	[0.274]
Type Of Flooring			0.764***	0.328***	0.966***	0.436***
			[0.172]	[0.068]	[0.185]	[0.076]
Telephone			1.226*	0.361	1.108*	0.358
			[0.699]	[0.241]	[0.669]	[0.238]
Country-year FE	Yes	Yes	Yes	Yes	Yes	Yes
Constant	13.733***	1.498***	2.173*	0.789**	0.170	0.172
	[0.092]	[0.520]	[1.177]	[0.390]	[1.312]	[0.436]
Obs = No. Of Areas	968	968	1,767	1,767	1,767	1,767
R-squared	0.415	0.736	0.618	0.610	0.583	0.577
Number Of Areas			968	968	968	968

Robust standard errors in brackets *** p<0.01, ** p<0.05, * p<0.1; [1]HH: Household

Note: All the variables are calculated at the area-level. See Section 3 for the construction of how geographic areas have been constructed. Socially-related projects include projects in the following Sectors (CRS code in parenthesis): Education (110); Health (120); Population Policies (130); Water Supply and Sanitation (140); Government and Civil Society (150); Other Social Infrastructure and Services (160); Women in Development (420); Developmental Food Aid (520); Non-Food Commodity Assistance (530).

Table A7: Robustness Test Main Results, OLS weighted (IWP) – Education Sector Projects

	(1)	(2)	(3)	(4)	(5)	(6)
	Ln (DHS Wealth Index)	DHS Wealth Index Quintiles	Average Years of Education	Average Education al Attainment	Max. Years of Education	Max. Educational Attainment
Treated (*D*) with Project	0.013	0.175***				
	[0.011]	[0.063]				
Treated*Survey Year (*D***T*)			0.585***	0.173***	0.585***	0.195***
			[0.168]	[0.054]	[0.183]	[0.058]
Most Recent Survey Year (*T*)			2.301***	0.364***	2.143***	0.238***
			[0.285]	[0.090]	[0.276]	[0.090]
Female-Headed HH[1]	0.069	0.904***	0.363	0.015	0.370	0.004
	[0.046]	[0.229]	[0.451]	[0.152]	[0.480]	[0.173]
Age Of HH members	0.001	0.016***	-0.072***	-0.023***	-0.041**	-0.013**
	[0.001]	[0.006]	[0.019]	[0.006]	[0.020]	[0.006]
HH Size	0.002	-0.075***	0.076	0.026	0.305***	0.101***
	[0.009]	[0.028]	[0.081]	[0.027]	[0.083]	[0.029]
No. Of Men in HH	0.017	0.261*	-0.505*	-0.162*	-0.379	-0.134
	[0.039]	[0.136]	[0.258]	[0.088]	[0.255]	[0.095]
Rural Area	-0.112***	-1.114***	-0.573**	-0.201***	-0.802***	-0.272***
	[0.017]	[0.110]	[0.239]	[0.078]	[0.283]	[0.091]
Dependency Ratio	0.458***	3.992***	2.379**	0.813**	3.269***	1.023***
	[0.119]	[0.588]	[1.070]	[0.336]	[1.161]	[0.361]
Access To Electricity			0.844**	0.270**	0.826*	0.206
			[0.391]	[0.129]	[0.426]	[0.142]
Radio			2.730***	0.803***	2.761***	0.824***
			[0.435]	[0.141]	[0.465]	[0.155]
Bicycle			0.174	-0.001	0.648	0.126
			[0.399]	[0.133]	[0.439]	[0.146]
Car			3.684***	1.244***	3.419***	1.193***
			[0.897]	[0.285]	[0.855]	[0.277]
Type Of Flooring			0.784***	0.334***	0.987***	0.443***
			[0.174]	[0.069]	[0.186]	[0.077]
Telephone			1.195*	0.349	1.094	0.357
			[0.697]	[0.242]	[0.665]	[0.237]
Country-year FE	Yes	Yes	Yes	Yes	Yes	Yes
Constant	13.731***	1.474***	2.139*	0.779**	0.130	0.158
	[0.091]	[0.525]	[1.182]	[0.392]	[1.314]	[0.435]
Obs = No. Of Areas	968	968	1,767	1,767	1,767	1,767
R-squared	0.415	0.734	0.618	0.610	0.584	0.579
Number Of Areas			968	968	968	968

Robust standard errors in brackets *** p<0.01, ** p<0.05, * p<0.1; [1]HH: Household

Note: All the variables are calculated at the area-level. See Section 3 for the construction of how geographic areas have been constructed. Education-related projects include projects in the CRS code 110.

III. Distribution And Intensity Of Chinese Foreign Assistance

Table A8. Number of projects (#) and total project amount (US constant $)

	Mean	**Median**	**25th percentile**	**75th percentile**
Number of projects	35.32	5	2	16
Total amount	551.67	107.66	37.71	252.98

Table A9: OLS weighted (MMWS) – Multilevel Treatment (Number Of Projects)

	(1)	(2)	(3)	(4)	(5)	(6)
	Ln (DHS Wealth Index)	DHS Wealth Index Quintiles	Average Years of Education	Average Educational Attainment	Max. Years of Education	Max. Educational Attainment
Treat-Level 1	0.066	-0.035				
	[0.047]	[0.113]				
Treat-Level 2	0.159***	0.117				
	[0.060]	[0.074]				
Treat-Level 3	0.016	0.408***				
	[0.049]	[0.063]				
Treat1*Survey Year			0.232	0.067	0.300	0.060
			[0.319]	[0.095]	[0.332]	[0.110]
Treat2*Survey Year			0.578**	0.139*	0.452*	0.120*
			[0.274]	[0.076]	[0.259]	[0.071]
Treat3*Survey Year			0.486**	0.169**	0.305	0.104
			[0.209]	[0.070]	[0.222]	[0.074]
Most Recent Survey Year			2.034***	0.358***	2.062***	0.321***
			[0.253]	[0.086]	[0.277]	[0.095]
Female-Headed HH[1]	0.702**	0.468**	0.891**	0.264**	0.876*	0.254*
	[0.351]	[0.196]	[0.415]	[0.131]	[0.453]	[0.143]
Age Of HH members	0.010	0.025***	-0.069***	-0.022***	-0.040**	-0.012**
	[0.009]	[0.006]	[0.015]	[0.005]	[0.016]	[0.005]
HH Size	0.097	-0.016	-0.058	-0.017	0.140*	0.049*
	[0.075]	[0.020]	[0.074]	[0.023]	[0.083]	[0.026]
No. Of Men in HH	0.015	0.287***	0.127	0.056	0.370	0.135
	[0.179]	[0.106]	[0.275]	[0.086]	[0.280]	[0.089]
Rural Area	-0.223***	-1.088***	-0.605***	-0.206***	-0.873***	-0.288***
	[0.047]	[0.075]	[0.208]	[0.065]	[0.233]	[0.072]
Dependency Ratio	1.976**	4.479***	2.803***	0.896***	3.769***	1.192***
	[1.001]	[0.440]	[1.071]	[0.313]	[1.160]	[0.340]
Access To Electricity			1.592***	0.488***	1.822***	0.533***
			[0.306]	[0.095]	[0.343]	[0.106]
Radio			2.183***	0.675***	2.322***	0.719***
			[0.430]	[0.124]	[0.458]	[0.135]
Bicycle			0.339	0.055	0.586	0.087
			[0.411]	[0.128]	[0.425]	[0.138]
Car			4.158***	1.367***	4.187***	1.323***
			[0.823]	[0.266]	[0.982]	[0.306]
Type Of Flooring			2.013***	0.734***	2.045***	0.760***
			[0.570]	[0.185]	[0.559]	[0.178]
Telephone			0.498***	0.190***	0.569***	0.229***
			[0.166]	[0.053]	[0.184]	[0.061]
Country-year FE	Yes	Yes	Yes	Yes	Yes	Yes
Constant	11.999***	0.488	2.534***	0.933***	0.658	0.345
	[1.194]	[0.420]	[0.978]	[0.313]	[1.094]	[0.347]
Obs = No. Of Areas	1,051	1,051	1,951	1,951	1,951	1,951
R-squared	0.163	0.669	0.621	0.615	0.579	0.566
Number Of Areas			1,051	1,051	1,051	1,051

Robust standard errors in brackets *** p<0.01, ** p<0.05, * p<0.1; [1]HH: Household

Note: All the variables are calculated at the area-level. See Section 3 for the construction of how geographic areas have been constructed.

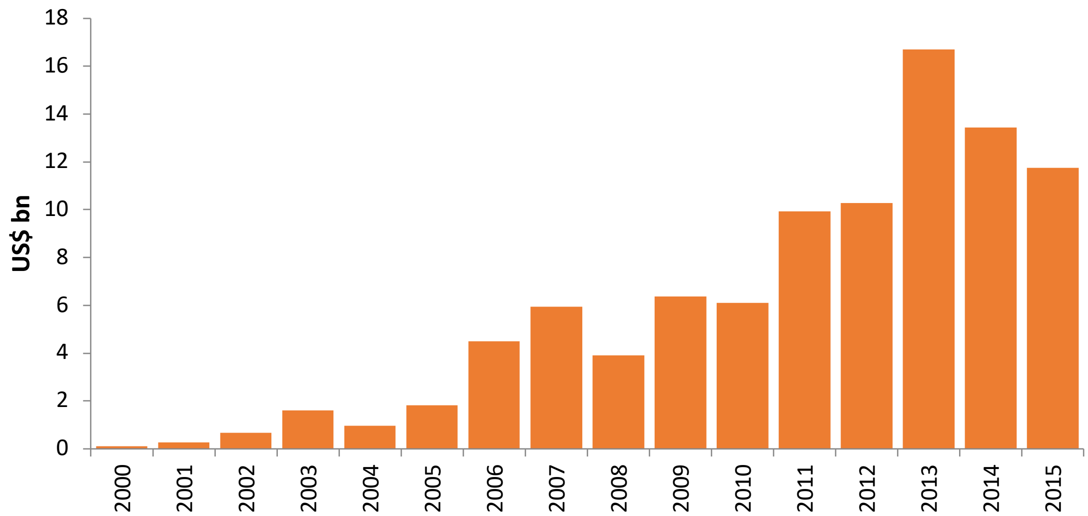
Table A10: OLS weighted (MMWS) – Multilevel Treatment (Financial Project Volume)

	(1)	(2)	(3)	(4)	(5)	(6)
	Ln (DHS Wealth Index)	DHS Wealth Index Quintiles	Average Years of Education	Average Educational Attainment	Max. Years of Education	Max. Educational Attainment
Treat-Level 1	0.168	-0.040				
	[0.117]	[0.120]				
Treat-Level 2	0.089**	0.152*				
	[0.035]	[0.089]				
Treat-Level 3	0.006	0.167**				
	[0.028]	[0.078]				
Treat1*Survey Year			0.533	0.149	0.379	0.122
			[0.371]	[0.154]	[0.477]	[0.199]
Treat2*Survey Year			0.134	0.080	0.019	0.056
			[0.221]	[0.071]	[0.257]	[0.077]
Treat3*Survey Year			0.466**	0.149**	0.352	0.115*
			[0.237]	[0.069]	[0.245]	[0.067]
Most Recent Survey Year			2.162***	0.398***	2.231***	0.373***
			[0.275]	[0.093]	[0.293]	[0.102]
Female-Headed HH[1]	0.422*	0.449**	0.464	0.150	0.476	0.161
	[0.240]	[0.188]	[0.433]	[0.140]	[0.483]	[0.159]
Age Of HH members	0.010	0.026***	-0.056***	-0.018***	-0.025	-0.008
	[0.007]	[0.006]	[0.014]	[0.004]	[0.016]	[0.005]
HH Size	0.077	-0.018	-0.056	-0.019	0.157**	0.051**
	[0.060]	[0.018]	[0.068]	[0.022]	[0.074]	[0.023]
No. Of Men in HH	-0.061	0.336***	0.277	0.106	0.556**	0.191**
	[0.144]	[0.114]	[0.268]	[0.084]	[0.256]	[0.081]
Rural Area	-0.175***	-1.069***	-0.659***	-0.232***	-0.860***	-0.297***
	[0.034]	[0.061]	[0.209]	[0.068]	[0.240]	[0.079]
Dependency Ratio	1.629**	4.991***	2.202**	0.799**	3.704***	1.260***
	[0.760]	[0.388]	[0.957]	[0.315]	[1.127]	[0.373]
Access To Electricity			1.789***	0.550***	1.892***	0.541***
			[0.301]	[0.095]	[0.337]	[0.107]
Radio			1.604***	0.480***	1.783***	0.557***
			[0.343]	[0.111]	[0.415]	[0.133]
Bicycle			0.647*	0.141	0.789**	0.150
			[0.355]	[0.115]	[0.380]	[0.126]
Car			3.882***	1.297***	3.826***	1.238***
			[0.808]	[0.262]	[0.920]	[0.287]
Type Of Flooring			1.675***	0.581***	1.749***	0.634***
			[0.593]	[0.196]	[0.582]	[0.188]
Telephone			0.412***	0.169***	0.561***	0.243***
			[0.150]	[0.051]	[0.168]	[0.060]
Country-year FE	Yes	Yes	Yes	Yes	Yes	Yes
Constant	12.392***	0.073	3.109***	1.126***	0.660	0.336
	[0.899]	[0.355]	[0.948]	[0.321]	[1.086]	[0.368]
Obs = No. Of Areas	1,051	1,051	1,951	1,951	1,951	1,951
R-squared	0.141	0.680	0.659	0.664	0.632	0.645
Number Of Areas			1,051	1,051	1,051	1,051

Robust standard errors in brackets *** p<0.01, ** p<0.05, * p<0.1; [1]HH: Household

Note: All the variables are calculated at the area-level. See Section 3 for the construction of how geographic areas have been constructed.

Figure A1. Distribution of Chinese Loans to Africa since 2000



Source: China-Africa Research Initiative, Johns Hopkins University (accessed on Dec 13, 2017, at: http://www.sais-cari.org/data-chinese-loans-and-aid-to-africa)

Figure A2. Number of projects along the different percentiles