

Foreign Aid Shapes Local Urban Development*

VINICIOS P. SANT'ANNA[†] CIHANG WANG[‡]

Cal Poly & MIT

University of Illinois

October 2, 2025

Abstract

We examine how foreign aid shapes urban development in Sub-Saharan Africa at the very local level. Using data on 1,643 georeferenced Chinese aid projects, we analyze the effect of aid on the evolution of built surface and volume on 100-meter grids within a 2-kilometer radius microregion. Our staggered difference-in-differences approach reveals that foreign aid projects significantly increase local urbanization, with the effects decreasing with distance from the projects. Treatment effects are mostly driven by residential development, particularly in previously underdeveloped areas. Our findings contribute to the understanding of the consequences of foreign aid on urban transformations in the developing world.

KEYWORDS: Foreign Aid, Urban Development, Sub-Saharan Africa.

JEL CLASSIFICATION: F35, O18, O19, R11.

*We are grateful to Dan Bernhardt, Greg Howard, and seminar participants at the University of Illinois for their helpful comments.

[†]Orfalea College of Business, California Polytechnic State University, and Massachusetts Institute of Technology, Urban Economics Lab. Email: santanna@calpoly.edu. Website: vpsantanna.com.

[‡]Department of Economics, University of Illinois at Urbana-Champaign. 214 David Kinley Hall, 1407 W. Gregory Dr, Urbana, IL 61801. Email: cwang153@illinois.edu. Website: sites.google.com/view/cihangwang

1 Introduction

Sub-Saharan Africa is one of the world’s fastest urbanizing regions. While the region’s population is projected to increase by 79%, reaching 2.2 billion by 2054, its urban population share is expected to increase from its current 40% to 60% by the 2050s (UN DESA, 2019, 2024). This striking urban transformation occurs alongside substantial foreign aid inflows, with Sub-Saharan Africa receiving over USD 36 billion in official development assistance from OECD countries in 2024 alone (OECD, 2025). Understanding how foreign aid shapes urbanization is crucial for designing effective development policies and managing the rapid urbanization process of the region.

This paper examines the impact of foreign aid on urbanization in Sub-Saharan Africa. While a vast literature has examined the consequences of foreign aid across multiple dimensions of the economy (Burnside and Dollar, 2000; Alesina and Weder, 2002; Rajan and Subramanian, 2008; Andrabi and Das, 2017), the literature has largely overlooked its role in shaping micro-level urban development patterns. This reflects, in part, the challenges in measuring urbanization at small geographic dimensions. In this paper, we overcome this challenge by combining georeferenced data from 1,643 foreign projects from the AidData initiative (Goodman et al., 2024) with 100-meter grid information on built-up surface and volume from the Global Human Settlement Layer (GHSL) datasets. This fine-grained dataset allows us to estimate the effects of aid on urbanization within relatively small microregions.

The primary empirical challenge in estimating the effects of foreign aid on urbanization is the potential endogeneity due to selection in the location of aid projects. Projects may be strategically located in countries, regions, or cities with stronger political connections, better baseline infrastructure, or more developed areas (Alesina and Dollar, 2000; Qian, 2015; Dreher et al., 2019). To address these endogeneity concerns, we leverage the highly detailed micro-level satellite-based urban structure information to implement a within-microregion empirical strategy. We define a microregion as the grid cells located within 2 kilometers (roughly 1.24 miles) surrounding the projects and compare the grids closer to the aid projects to those farther away. This spatial quasi-experimental design allows us to control for unobserved local-level confounders that may jointly influence the location choice of aid projects and urban development. Our approach differs from existing studies that use satellite data at more aggregate levels, which are more susceptible to suffering from endogeneity issues raised in the literature (Bomprezzi et al., 2024; Lindlacher and Pirich, 2024; Bluhm et al., 2025).

Leveraging the staggered implementation of aid projects, we find that foreign aid generates significant increases in local urban development. Proximity to aid projects significantly increases both the surface area and volume of urban construction, with the effects declining sharply with distance and becoming statistically insignificant beyond approximately 1.5 kilometers (1.93 miles) from the project site. Each additional 100 meters of distance from an aid project is associated with an average of 2.3 fewer square meters of built surface and 15.6 fewer cubic meters of built volume. Using binary treatment definitions with alternative distance thresholds, we consistently find that areas closer to aid projects experience increases of 17–24 square meters in built surface and 118–178 cubic meters in built volume, on average per grid. Our results are robust to multiple alternative specifications and definitions of treated and control areas.

We also conduct an event study design that reveals important insights about the dynamics of aid effects on urbanization and provides a crucial assessment of potential pre-trends in urbanization of areas closer to aid projects relative to those farther. We find no evidence of differential pre-treatment trends between areas closer to and farther from project sites, suggesting that treated and control areas followed parallel urbanization trajectories before aid implementation. This absence of pre-trends strongly supports our identifying assumption that project location within microregions is plausibly exogenous once we condition the analysis on our demanding set of fixed effects. Following aid implementation, treatment effects emerge sharply and grow steadily over time, reaching approximately 30 square meters of additional built surface and 260 cubic meters of additional built volume after 15 years. This sustained growth pattern suggests that aid projects create persistent shifts in local urbanization rates rather than temporary construction booms, with areas closer to projects continuing to urbanize faster than more distant areas within the same microregion throughout the post-treatment period.

When assessing the heterogeneity of our results, we find that these effects are overwhelmingly driven by residential rather than commercial development, suggesting that aid projects tend to be associated with local amenities that attract households. The effects are most pronounced in initially underdeveloped areas, where more land is available for development, and where housing supply tends to be more elastic (Saiz, 2010; Baum-Snow and Han, 2024). Surprisingly, the amount of aid in dollars does not seem to have a differential impact on urbanization.

Contributions to the literature. This paper contributes to the literature on the impacts of foreign aid on economic growth and urbanization (Clemens et al., 2012; Galiani et al., 2017; Dreher et al., 2021a). Many studies have used geospatial impact evaluation methods to study how foreign aid can affect structural transformation, infrastructure development, and the spatial distribution of economic activities. To study these effects, many have relied on satellite images of nighttime light intensity to measure economic activity and urbanization. While it has been shown that nighttime imagery can be a reliable measure (Chen and Nordhaus, 2011; Henderson et al., 2012; Donaldson and Storeygard, 2016; Bluhm and Krause, 2022), it imposes limits at the granularity level of analysis, primarily because of challenges in distinguishing light intensity at small grids. Therefore, most studies that use this information are limited to studying grids of about 30-50 kilometers (Dreher and Lohmann, 2015; Dreher et al., 2021b; Bitzer and Gören, 2024; Lindlacher and Pirich, 2025). We contribute to this literature by examining the impact of foreign aid at a very local level, allowing us to conduct an empirical assessment that alleviates many of the endogeneity concerns of the literature.

This paper also contributes to the literature on the determinants of urbanization patterns in developing-world cities (Baum-Snow et al., 2017; Harari, 2020; Harari and Wong, 2025), especially in Sub-Saharan Africa (Bryan et al., 2020; Henderson et al., 2021). A growing body of work has investigated how demographic change, geographic barriers, agricultural productivity, natural resource booms, and climate shocks shape urban development in the region (Becker and Morrison, 1988; Lian and Lejano, 2007; Henderson et al., 2012; Nunn and Puga, 2012; Storeygard, 2016; Jedwab et al., 2017).¹ Our contribution consists of examining the role of foreign aid in shaping the local urbanization process.

Our findings also provide valuable insights that can inform current policy debates on the impact of foreign aid in developing countries. The importance and effectiveness of foreign assistance have re-entered the policy debate in light of recent reductions in global aid OECD (2025) and significant cuts to the United States Agency for International Development (USAID). While previous studies show that foreign aid can significantly increase economic growth (Dreher et al., 2021a) improve education and reduce child mortality (Martorano et al., 2020), our findings suggest that foreign aid projects may also be associated with local amenities that make locations near the projects more attractive to residents, leading to a permanent shift in local urbanization.

¹For a comprehensive review of the underlying forces shaping urbanization in developing countries, see Marx et al. (2013).

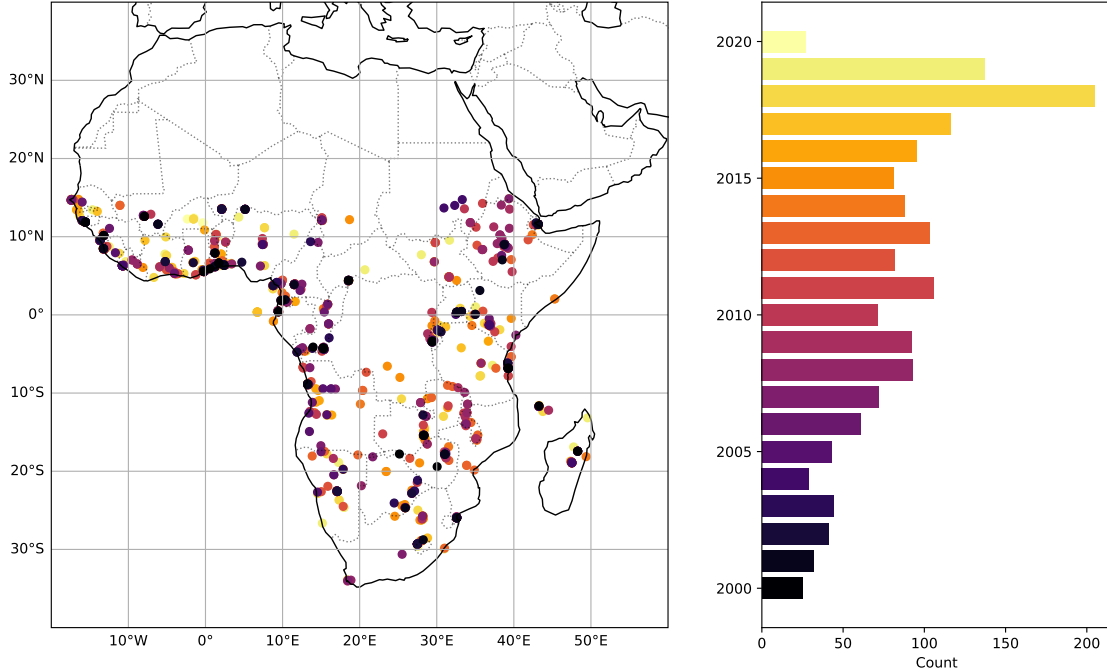


Figure 1. Space and Time distributions of Aid Projects. This figure illustrates the geographic distribution of the development projects in Africa between 2000 and 2020 (on the left) and the distribution by commitment year (on the right). The colors represent the commitment year of projects, with lighter colors indicating more recent years. Our sample consists of 1,643 projects and includes only those completed by 2023 with a radius footprint smaller than 500 meters.

2 Data

AidData. We use AidData’s Geospatial Global Chinese Development Finance Dataset, Version 3.0 (Goodman et al., 2024) to identify foreign aid projects and their precise locations. The dataset provides comprehensive geospatial information on development projects supported by Chinese loans and grants worldwide between 2000 and 2021. We focus our analysis solely on projects located in Sub-Saharan Africa that were classified as completed by 2023. We also exclude projects from our sample that have a footprint radius exceeding 500 meters (0.31 miles), to avoid including very large projects that may have a different influence on local urbanization dynamics. Our sample consists of 1,643 aid projects across 44 countries, representing over \$46 billion (Constant USD 2021) in investment. Figure 1 displays the spatial (left panel) and temporal (right panel) distributions of these projects, showing substantial geographic coverage across Sub-Saharan Africa, with growing implementation over the sample period. The average project has a footprint of a 100-meter radius and is associated with an investment of US\$57 million. A typical project in our sample is either a school, a hospital, or an industrial park.²

²For more details on the descriptive statistics of the projects, see Appendix A in the online appendix.

GHSL Global Built-up Datasets We measure urban development using the Global Human Settlement Layer (GHSL) from the European Commission’s Joint Research Centre. The raster data represents the spatial distribution of built-up surfaces [Pesaresi and Politis \(2023a\)](#) and volume [Pesaresi and Politis \(2023b\)](#). The information is obtained from Earth Observation (EO) data, specifically leveraging Sentinel-1 and Landsat imagery.³ The dataset spans the period from 1975 to 2020, with snapshots every five years, and offers a spatial resolution of 100-meter (328 feet) grid cells. The dataset also includes the classification of the percentage of built-up surfaces and volumes per grid into residential and non-residential categories.⁴ The average grid in our data has 1,900 square meters of built surface and 17,455 cubic meters of built volume, predominantly residential. At the microregion level (2 km radius), project areas averaged 2.5 million square meters of built surface and 22.8 million cubic meters of volume, with 5-year growth rates of 10-11% in the baseline period before receiving the project.⁵

Despite the well-documented “income bias” (lower-income regions tend to exhibit lower classification accuracy) in remote-sensing-based measurements, the GHSL BUILT-S R2023 product outperforms all alternative sources, achieving 55.56% higher predictive accuracy than the best non-GHSL option in the low-income stratum. This accuracy is made possible by the integration of 10-meter Copernicus Earth Observation data into the production system, which facilitates effective gap filling, temporal continuity and methodological repeatability. Comparative evaluations show that GHSL R2023 is among the most accurate at distinguishing built-up from non-built-up areas at 10-meter resolution and the top-performing predictor of continuous built-up surface area at 100-meter resolution. Volume layer is constructed as the product of the gross built-up surface by the building height, in which GHSL R2023 also excels predicting, and inherits the validity of the two metrics as well ([Pesaresi et al., 2024](#)).

3 Empirical Strategy

The major challenge in estimating the causal impact of foreign aid on local urbanization is the potential endogeneity of project’s location choice. Previous research shows that foreign aid to

³Sentinel-1 is a radar-based Earth observation mission developed by the European Space Agency (ESA). It operates using synthetic aperture radar (SAR), which enables the acquisition of high-resolution imagery regardless of weather conditions or daylight. The Landsat program, initiated in 1972 and managed by NASA and the U.S. Geological Survey (USGS), provides multispectral optical imagery of the Earth’s surface.

⁴Non-residential use classification is done by Sentinel-2 imagery (10-meter resolution), trained with reference data such as Microsoft/Facebook building footprints and OpenStreetMap, and aggregated to 100-meter resolution.

⁵For more descriptive statistics of projects, grids, and microregions, see [Table A.1](#) in the Online appendix.

a country or region tends to be heavily influenced by political or strategic considerations, such as colonial history and political alliances (Alesina and Dollar, 2000; Qian, 2015; Dreher et al., 2019). Moreover, foreign aid may flow disproportionately to fast-growing regions and cities as a way to maximize project impact (World Bank, 2012).

We address this endogeneity concern by adopting a within-microregion spatial design. For each project, we define a 2-kilometer radius area from the project’s centroid as a microregion, our basic area of analysis. Our empirical strategy contrasts the evolution of urbanization in grids closer to the project with that of grids farther away but within the same microregion. This approach enables us to control for unobserved factors at the microregion-by-time level that may influence both project location and urban development. Our high-resolution 100-meter grid data enables this granular comparison, a key advantage over existing studies using nighttime light datasets, which typically span grids with sizes between 30 and 50 kilometers. We later provide evidence validating our identifying assumption that there were no pre-treatment trends in urbanization associated with the proximity to the project’s location.

Therefore, our empirical setting consists of a staggered implementation of 1,643 aid projects across Sub-Saharan Africa. Multiple recent studies have demonstrated potential biases in the two-way fixed effects estimators with staggered treatment (Callaway and Sant’Anna, 2021; Goodman-Bacon, 2021; Sun and Abraham, 2021). To avoid these biases, we adopt the stacked regression estimator, where we stack implementation cohort-specific data, and the grid- and time-fixed effects are saturated with indicators for project identifiers (Cengiz et al., 2019; Baker et al., 2022).

3.1 Urbanization and Distance to Projects

We begin by investigating the relationship between distance to a project and the urbanization of areas within a microregion. We estimate the following specification:

$$y_{rit} = \alpha_{ri} + \alpha_{rt} + \sum_{d=1}^{d=19} \beta_d \cdot \mathbb{1}(D_{ri} = d) \times Post_t + \epsilon_{rit}, \quad (1)$$

where $\mathbb{1}(D_{ri} = d)$ is a binary that equals one if grid i in microregion r is located at distance group d (for every 100 meters) from the project boundary. The omitted category is grids beyond 1,900 meters. $Post$ is the binary variable equal to one for all periods after the project’s commitment year.⁶ We opt to use the commitment date as the treatment period because it represents the

⁶The data provides the date of commitment, implementation, and completion date.

earliest credible signal to residents and potential investors about future aid projects in the area. It helps mitigate endogeneity concerns arising from construction-related factors that may influence the actual starting date for the project or generate anticipation effects. y_{rit} is either the built surface in square meters or the built volume in cubic meters of grid i , located in microregion r , at time t . α_{ri} is a vector of microregion-by-grid-specific binary variables. This set of dummies enables us to control for time-invariant, grid-specific factors that may influence urbanization. For instance, geographic features such as the presence of rivers, lakes, mountains, and wetlands can constrain the availability of developable land (Saiz, 2010). α_{rt} is a vector of microregion-by-time binary variables that capture factors common to all grids within a microregion at any point in time, such as economic shocks and local policy or regulation changes. Note that because each microregion is defined as a 2 km radius around a project, microregion dummies are perfectly collinear with project dummies. To avoid contaminating the estimate with the mechanical increase in the built surface and volume of the project itself, we exclude from the sample all grids located within the project radius. We cluster the standard errors at the microregion level in all specifications, allowing for flexible spatial and temporal correlation among grids within a microregion.

3.2 Average Treatment Effect of Foreign Aid on Urbanization

Next, we assess the average treatment effect of foreign aid projects on the local evolution of urbanization. We begin by estimating a “continuous treatment” difference-in-differences specification:

$$y_{rit} = \alpha_{ri} + \alpha_{rt} + \delta_D \cdot Distance_{ri} \times Post_t + \epsilon_{rit}, \quad (2)$$

where $Distance_{ri}$ is the distance in meters between the centroid of grid i and the centroid of the project located in microregion r . The parameter δ_D captures the average effect of distance to projects on local urbanization within a microregion area. The remaining terms are defined as before.

To gain further insights into the average treatment effect on grids located sufficiently close to the projects, we explore an alternative approach based on a spatial differences-in-differences design. Based on the previous estimates, we can define a spatial threshold θ and consider all grids located within a distance θ from the project as treated, while those located at a distance greater than θ are defined as control units. We employ the following specification:

$$y_{rit} = \alpha_{ri} + \alpha_{rt} + \delta_\theta \cdot Treated_{ri}(\theta) \times Post_t + \epsilon_{rit}, \quad (3)$$

where $Treated_{ri}(\theta)$ equals one if grid i is within distance θ from the project in microregion r . α_{ri} and α_{rt} are the same set of binary variables as defined before. δ_θ captures the average treatment effect (ATT) for a given treatment threshold θ . We examine multiple thresholds (1 km, 1.25 km, 1.5 km) to assess robustness. To address potential spillovers in the grids around the treatment threshold, we also conduct a “donut” design. We exclude grids between 1 and 1.5 km, defining the grids within 1 km of the project as treated and those with distances beyond 1.5 km as control units.

We also conduct an event-study design to investigate the dynamics of these effects and evaluate differences in trends between the treated and control units before treatment. We estimate the following specification:

$$y_{rit} = \alpha_{ri} + \alpha_{rt} + \sum_{\tau \neq -5} \beta_{\theta\tau} \cdot Treated_{ri,t-\tau}(\theta) + \epsilon_{rit}, \quad (4)$$

where $Treated_{ri,t-\tau}(\theta)$ is an indicator variable for treatment time τ . We estimate the above specification using a 15-year window before and after the aid project, with the period 5 years preceding the event as the reference. The other terms are defined as before, and standard errors are clustered at the microregion level.

4 Results

4.1 Distance Gradient

We begin our analysis by examining how the urbanization effects of foreign aid vary with distance from the project. [Figure 2](#) presents the estimated coefficients β_d from [eq. \(1\)](#) for built surface (Panel A) and volume (Panel B). Our findings reveal that the presence of foreign aid projects increases urbanization at the local level with a clear spatial decay pattern—grids closer to projects experience larger increases in both built surface and volume compared to the farthest areas. On average, built surface increases by 20-55 square meters per grid in areas closer to the projects, with an approximately linear decline with distance. Built volume increases on average by around 200 cubic meters per grid up to approximately 1 km from the project site, after which it begins to decline more sharply.⁷ Importantly, the effects become statistically insignificant beyond approximately 1.3 to 1.5 kilometers from projects, providing empirical guidance for defining treatment and control areas in our subsequent analysis.

⁷In the online appendix, we explore the heterogeneity of the distance gradients by project type. [Figures C.3](#) and [C.4](#) shows that these distance gradients vary substantially across types.

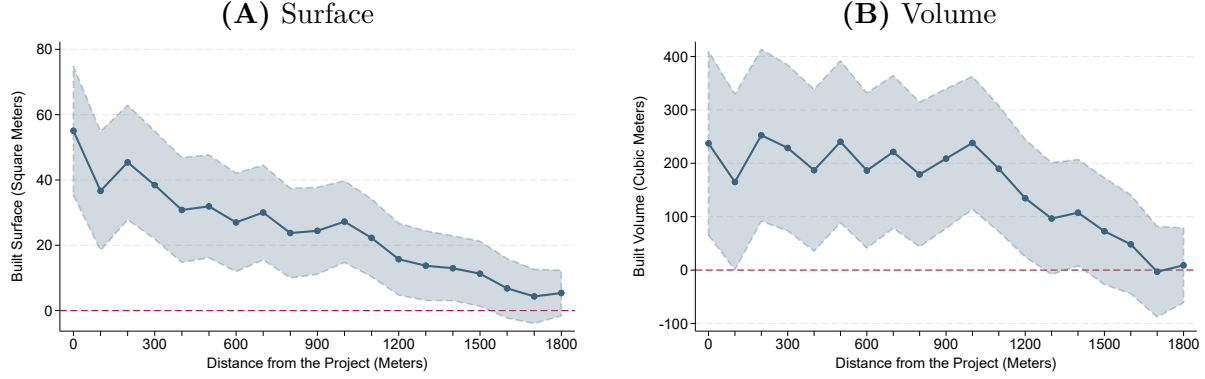


Figure 2. Distance Gradient. This figure plots the estimated coefficients of distance dummies for every 100 meters away from the center of the project location and 95% confidence intervals according to the specification in equation (1). Panel A shows the estimates for built-up surface in square meters per grid, while Panel B shows the coefficients for volume in cubic meters per grid.

4.2 Average Treatment Effect Estimates

Table 1 presents our main difference-in-differences estimates of aid projects’ impact on local urbanization. Panel A reports the effect for built surface and Panel B reports the effect for built volume. Column (1) shows the estimates of Eq. (2), where we use distance to projects as a continuous treatment. The results indicate that each additional 100 meters of distance from a project is associated with 2.3 fewer square meters per grid of built surface and 15.6 fewer cubic meters per grid of built volume. These estimates provide a baseline measure of the spatial decay rate of urbanization effects.

Columns (2) through (4) present results from the binary treatment specifications in eq. (3), using alternative thresholds for treatment (1km, 1.25km, and 1.5km, respectively). Column (5) applies the “donut strategy”, excluding the grids between 1 km and 1.5 km from the projects. Across all specifications, we find large and statistically significant effects on both surface and volume. The estimates range from an increase of 17 to 24 square meters per grid in built surface and an increase of 118 to 178 cubic meters per grid in built volume. The consistency of results across different threshold definitions suggests that our findings are robust to alternative ways of defining treatment exposure. These results reinforce the findings from the distance-gradient analysis, confirming that foreign aid generates substantial and localized urban development effects.

To contextualize our findings, we perform a back-of-the-envelope calculation that aggregates the estimated per-grid increases in built-up surface and volume into total expected effects within the 1.5 km threshold per project. As Table 1 shows, the average treatment effects within a 1.5 km radius are 17.3 square meters of built-up surface and 145.8 cubic meters of built-up volume per

treated grid. On average, each project has 806 treated grids under this cutoff.⁸ Multiplying per-grid effects by the average number of treated grids yields an average aggregate increase of approximately 14 thousand square meters of built surface and over 117 thousand cubic meters of volume in the treated area relative to those beyond 1.5 kilometers away from the projects. These numbers help to illustrate the sizable and highly localized urban expansion responses to foreign aid projects.

Table 1. Average Effect of Aid Projects on Urbanization.

Panel A. Built Surface					
	Distance to Project (Meters) (1)	Treatment Threshold at 1 km (2)	Treatment Threshold at 1.25 km (3)	Treatment Threshold at 1.5 km (4)	Treatment "Donut" Design (5)
Distance \times Post	-0.023*** (0.005)				
Treated \times Post		18.190*** (4.226)	19.164*** (3.931)	17.259*** (3.662)	23.778*** (5.229)
Observations	14,459,624	14,459,624	14,459,624	14,459,624	9,555,345
Units	2,066,620	2,066,620	2,066,620	2,066,620	1,365,692
Periods	7	7	7	7	7
Clusters	1,643	1,643	1,643	1,643	1,643
R-squared	0.97	0.97	0.97	0.97	0.97

Panel B. Built Volume					
	Distance to Project (Meters) (1)	Treatment Threshold at 1 km (2)	Treatment Threshold at 1.25 km (3)	Treatment Threshold at 1.5 km (4)	Treatment "Donut" Design (5)
Distance \times Post	-0.156*** (0.043)				
Treated \times Post		117.857*** (38.678)	149.729*** (36.121)	145.768*** (33.769)	177.753*** (48.011)
Observations	14,459,624	14,459,624	14,459,624	14,459,624	9,555,345
Units	2,066,620	2,066,620	2,066,620	2,066,620	1,365,692
Periods	7	7	7	7	7
Clusters	1,643	1,643	1,643	1,643	1,643
R-squared	0.98	0.98	0.98	0.98	0.98

Notes: This table presents simple difference-in-differences estimates of the effects on the urbanization of grids based on the different treatment thresholds according to the specification in equation (3). The dependent variable is the built surface in Panel A and the built volume in Panel B. Column (1)-(3) shows the estimate using 1 kilometer, 1.25 kilometers, and 1.5 kilometers as the treated regions, while Column (4) displays the estimate using the “donut strategy”. The coefficient is the relative effect of the foreign aid project on urbanization of grids within the chosen threshold compared to the outskirts region. Robust standard errors clustered at the level of projects are in parentheses. Statistical significance: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

⁸The number of treated grids varies by project due to differences in project size. Recall that we define a treated grid as any 100m \times 100m pixel that falls within the area between the project radius and the 1.5 km buffer.

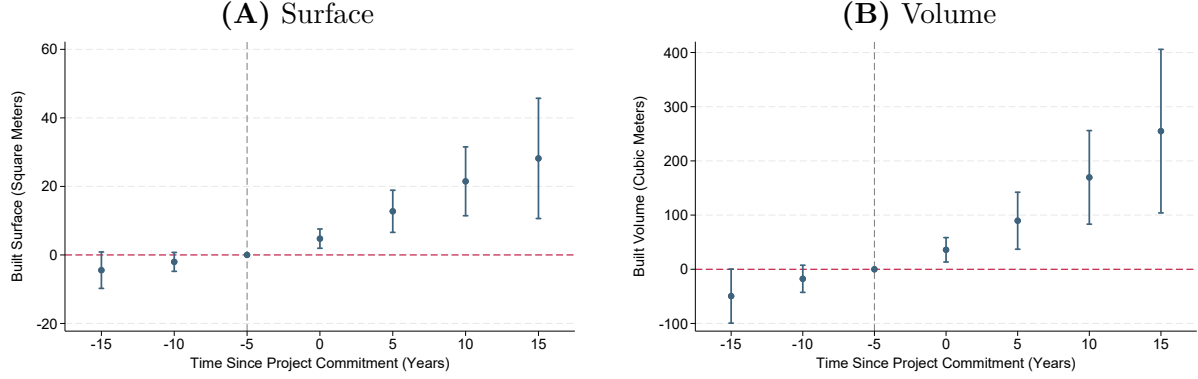


Figure 3. Event Study Specification. This figure plots the estimated coefficients and 95% confidence intervals for the event study specification using 1.5km as the treatment cut-off corresponding to the specification in equation (4). The coefficients represent the difference between built surface or volume within and beyond the treatment threshold surrounding the project location from 15 years before to 15 years after the establishment year of the project. Panel A shows the estimates for built-up surface in square meters per grid, while Panel B shows the coefficients for volume in cubic meters per grid. [Appendix B](#) shows the event study estimates using alternative thresholds to define treated and control units.

[Figure 3](#) plots the estimated coefficients on the event-time indicator using 1.5 km as the treatment cutoff, with results robust to alternative choices for the treatment threshold.⁹ The results provide strong support for our identification strategy and reveal important insights about the dynamics of aid effects on urban development.

The estimated coefficients for all pre-treatment periods are small and statistically insignificant, indicating that the treated and control grids followed parallel urbanization trends before the project implementation. This finding validates our core identifying assumption and rules out concerns that our results are driven by pre-existing differential trends between areas closer to and farther from project sites. After treatment, we observe a sharp and statistically significant treatment effect that grows steadily over time. On average, built surface increases by approximately 30 square meters per grid, and built volume rises by about 260 cubic meters per grid after 15 years of the project’s implementation. These dynamics suggest that aid projects generate a persistent shift in local urbanization trajectories, with areas closer to projects urbanizing at a faster rate relative to farther areas.¹⁰

4.3 Heterogeneity Analysis

The previous sections show that foreign aid has a positive effect on urbanization rates at the very local level. In [Table 2](#), we assess the potential heterogeneity of the estimates across multiple dimen-

⁹ [Figures B.1](#) and [B.2](#) show the results for the alternative treatment definitions.

¹⁰ [Figures C.5](#) and [C.6](#) in the appendix illustrate the event study specifications when estimated separately for each project type for surface and volume, respectively.

sions, revealing important insights about when and where foreign aid most effectively stimulates urbanization. Panel (A) shows the results for surface, while Panel (B) shows the results for volume.

In columns (1) and (2), we estimate a similar specification as in [Eq. \(3\)](#), but decomposing the dependent variable into residential and non-residential buildings, respectively. We find that our results are overwhelmingly driven by residential development. Residential built surface increases by approximately 15 square meters per grid and volume by 122 cubic meters per grid, while non-residential development shows much smaller effects (2.4 square meters per grid and 24 cubic meters per grid, respectively). Our findings suggest that foreign aid projects tend to generate positive local amenities that attract disproportionately more residential development. Previous studies have shown that residential sorting may be driven by local amenities ([Bayer et al., 2007](#); [Diamond, 2016](#); [Almagro and Domínguez-Iino, 2025](#)). Our paper is the first to show empirical evidence that foreign aid projects may also drive the provision of local amenities that shape local urban development. Future research could explore the precise mechanisms through which foreign aid projects may directly or indirectly trigger more local residential development.

In columns (3) to (5), we group foreign aid projects or microregions *ex-ante* by major observed characteristics, and we conduct a triple-difference specification to test whether some microregions or projects are more effective in generating urbanization. In columns (3) and (4), we group microregions by their level of urbanization five years prior to treatment. We first aggregate grids to a microregion level by taking the built sum (column 3) or the median grid (column 4), and then classify microregions as low if their measures were below the median measure across all 1,643 microregions. We find that areas with initially low built-up development experience dramatically larger treatment effects. The interaction terms indicate that low-development areas see differential increases of 44-49 additional square meters per grid of surface and 281-323 additional cubic meters per grid of volume compared to more developed areas. These results align with the fundamental differences in development constraints and costs for less developed areas. In less urbanized areas, with abundant developable land, aid projects can catalyze new construction at relatively low cost, with ample space for both surface and volume expansion. This finding has significant implications for aid targeting, suggesting that projects located in underdeveloped areas can have a greater impact on urbanization.

In Column (5), we test for heterogeneity in the effects by the amount of aid investment in dollars. We group projects into high amount as those with values above the median. Most surprisingly, our results demonstrate that project amounts are statistically insignificant

Table 2. Heterogeneity Analysis.

Panel A. Built Surface					
	Residential Built Surface (1)	Non-Residential Built Surface (2)	Low Built Region (Sum) (3)	Low Built Region (Median) (4)	High Project Amount (5)
Treated \times Post	14.894*** (3.639)	2.366*** (0.408)	-4.381 (4.592)	-6.617 (4.613)	17.844** (7.471)
\times Low Built Surface (Sum)			44.020*** (7.248)		
\times Low Built Surface (Median)				48.673*** (7.229)	
\times High Amount					2.383 (9.783)
Observations	14,459,624	14,459,624	14,459,624	14,459,624	7,192,652
Units	2,066,620	2,066,620	2,066,620	2,066,620	1,028,004
Periods	7	7	7	7	7
Clusters	1,643	1,643	1,643	1,643	818
R-squared	0.97	0.98	0.97	0.97	0.98

Panel B. Built Volume					
	Residential Built Volume (1)	Non-Residential Built Volume (2)	Low Built Region (Sum) (3)	Low Built Region (Median) (4)	High Project Amount (5)
Treated \times Post	122.122*** (33.532)	23.646*** (3.981)	-11.034 (47.457)	8.337 (49.037)	177.992*** (66.376)
\times Low Built Volume (Sum)			322.723*** (66.915)		
\times Low Built Volume (Median)				280.679*** (66.994)	
\times High Amount					-74.911 (85.792)
Observations	14,459,624	14,459,624	14,459,624	14,459,624	7,192,652
Units	2,066,620	2,066,620	2,066,620	2,066,620	1,028,004
Periods	7	7	7	7	7
Clusters	1,643	1,643	1,643	1,643	1,643
R-squared	0.98	0.99	0.98	0.98	0.98

Notes: This table reports the heterogeneous effects of foreign aid projects on grid-level urbanization. Column (1) and (2) display separate analyses for residential and non-residential built surface. Column (3)-(4) report the heterogeneity effects for low initial built-up. Column (5) reports the heterogeneity effect for high project amount spent. The dependent variable is the built surface in Panel A and the built volume in Panel B. The coefficients in (3)-(5) measure the differential treatment effect for regions with above-median (mean) initial level of urbanization or project spending compared to regions with below-median (mean) levels. Robust standard errors clustered at the level of projects are in parentheses. Statistical significance: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

for both surface and volume. This suggests that the financial scale of foreign aid projects is not a major driver of local urban development.¹¹

¹¹A simple cross-sectional regression suggests that less developed regions tend to receive a greater number of projects and higher per-project amount, conditional on project size, commitment year, and country fixed effects.

5 Additional Results

To provide a better understanding of how foreign aid affects local urban development, we conduct several additional analyses that examine both the mechanisms driving our main results and their heterogeneity across different types of projects. The results are discussed and presented in more details in [Appendix C](#).

First, we investigate whether the increases in built volume are simply reflecting the horizontal expansion of buildings. By definition, the expansion of built surface also lead to some expansion of the built volume. Therefore, because the effects on built volume mix both the extensive margin effects (more buildings) and intensive margin effects (taller buildings), this test helps us better understand the nature of urban densification around aid projects. Using a measure of average building height (built volume divided by built surface), we find that foreign aid significantly increases average building height, indicating that the volume effects also capture densification rather than simply horizontal expansion. These results suggest that foreign aid projects also create economic incentives for more efficient land utilization in areas closer to them relative to those farther away.

Second, we examine heterogeneity across project types to identify which categories of foreign aid interventions are most effective at stimulating local urbanization. This analysis is crucial for policy design, as it can inform the strategic allocation of development assistance. Our results reveal substantial heterogeneity, with *economic development and trade* projects showing the strongest urbanization effects, followed by *education, social infrastructure and services*, and *health* projects. In contrast, *emergency and humanitarian assistance* projects show negative effects, consistent with their deployment in areas experiencing distress or population displacement.

6 Conclusion

This paper provides new empirical insights into how foreign aid reshapes urban landscapes in Sub-Saharan Africa using fine-grained spatial data to identify local urbanization with greater precision than previously possible. By leveraging 100-meter grid cells rather than broader administrative units or coarser satellite pixels, we observe highly localized changes in the built environment in response to foreign aid that would otherwise be masked by aggregate analysis. Our findings demon-

This result further confirms our finding that it is the developmental stage of the region rather than the project value alone that drives the observed local urbanization process. However, we note that our measure captures only the direct urbanization response in the immediate vicinity of projects. Larger projects may have broader aggregate effects or generate different types of economic responses that our very local-level analysis does not capture.

strate that foreign aid projects generate substantial and persistent increases in local urbanization, with treatment effects reaching approximately 30 square meters of additional built surface and 260 cubic meters of additional built volume per grid after 15 years.

Our analysis reveals several important mechanisms through which aid influences local urbanization. The effects are overwhelmingly driven by residential rather than commercial development, suggesting that aid projects create local amenities that make areas more attractive to households and shift residential location preferences. This residential sorting response indicates that aid projects may generate positive spillovers beyond their direct contributions to the local community. We also find that effects are strongest in initially underdeveloped areas where developable land is more available and housing supply is more elastic, highlighting the importance of local geographic and economic constraints in determining aid effectiveness to local urbanization. We do not find evidence that the dollar amount of aid projects generates heterogeneous responses to urbanization.

From a methodological perspective, our within-microregion spatial design addresses key endogeneity concerns that have challenged previous studies in this literature. The absence of pre-treatment trends in our event study analysis, combined with the sharp spatial decay of effects, provides strong support for our identification strategy and suggests that our results capture causal impacts rather than confounding factors. Moreover, our results are robust to a battery of alternative specifications and definitions of treated and control areas.

These findings have important implications for aid policy and the broader development challenge facing Sub-Saharan Africa. Our results suggest that strategic placement of aid projects, particularly in less developed areas, can effectively catalyze local urban development. Importantly, we find that the financial scale of projects matters less than their presence and type, indicating that distributing aid across more locations may be more effective in spurring urban development than concentrating large investments in fewer places.

However, our study also highlights important limitations and areas for future research. Our analysis captures only the immediate spatial effects within 2 kilometers of project sites and does not assess broader aggregate impacts or general equilibrium effects. Future research should examine the longer-term sustainability of these urbanization effects, investigate the precise channels through which aid creates local amenities, and assess whether aid-induced urbanization translates into sustained economic development.

References

- Alesina, Alberto and Beatrice Weder**, “Do corrupt governments receive less foreign aid?,” *American economic review*, 2002, *92* (4), 1126–1137.
- and **David Dollar**, “Who gives foreign aid to whom and why?,” *Journal of Economic Growth*, 2000, *5* (1), 33–63.
- Almagro, Milena and Tomás Domínguez-Iino**, “Location sorting and endogenous amenities: Evidence from amsterdam,” *Econometrica*, 2025, *93* (3), 1031–1071.
- Andrabi, Tahir and Jishnu Das**, “In aid we trust: Hearts and minds and the Pakistan earthquake of 2005,” *Review of Economics and Statistics*, 2017, *99* (3), 371–386.
- Athey, Susan and Guido W Imbens**, “The state of applied econometrics: Causality and policy evaluation,” *Journal of Economic perspectives*, 2017, *31* (2), 3–32.
- Baker, Andrew C., David F. Larcker, and Charles C.Y. Wang**, “How much should we trust staggered difference-in-differences estimates?,” *Journal of Financial Economics*, 2022, *144* (2), 370–395.
- Baum-Snow, Nathaniel and Lu Han**, “The microgeography of housing supply,” *Journal of Political Economy*, 2024, *132* (6), 1897–1946.
- , **Loren Brandt, J Vernon Henderson, Matthew A Turner, and Qinghua Zhang**, “Roads, railroads, and decentralization of Chinese cities,” *Review of Economics and Statistics*, 2017, *99* (3), 435–448.
- Bayer, Patrick, Fernando Ferreira, and Robert McMillan**, “A unified framework for measuring preferences for schools and neighborhoods,” *Journal of political economy*, 2007, *115* (4), 588–638.
- Becker, Charles M. and Andrew R. Morrison**, “The Determinants of Urban Population Growth in Sub-Saharan Africa,” *Journal of Development Economics*, 1988, *27* (2), 259–278.
- Bitzer, Jürgen and Erkan Gören**, “The impact of foreign aid on local development: A grid cell analysis,” *The Journal of Development Studies*, 2024, *60* (10), 1557–1591.
- Bluhm, Richard and Melanie Krause**, “Top lights: Bright cities and their contribution to economic development,” *Journal of Development Economics*, 2022, *157*, 102880.
- , **Axel Dreher, Andreas Fuchs, Bradley C. Parks, Austin M. Strange, and Michael J. Tierney**, “Connective Financing: Chinese Infrastructure Projects and the Diffusion of Economic Activity in Developing Countries,” *Journal of Urban Economics*, 2025, *145*, 103730.
- Bompreszi, Pietro, Axel Dreher, Andreas Fuchs, Teresa Hailer, Andreas Kammerlander, Lennart C. Kaplan, Silvia Marchesi, Tania Masi, Caroline Robert, Charlotte Robert, and Kerstin Unfried**, “Wedded to Prosperity? Informal Influence and Regional Favoritism,” *SSRN Electronic Journal*, March 2024.
- Bryan, Gharad, Edward Glaeser, and Nick Tsivanidis**, “Cities in the Developing World,” *Annual Review of Economics*, 2020, *12*, 273–297.
- Burnside, Craig and David Dollar**, “Aid, policies, and growth,” *American economic review*, 2000, *90* (4), 847–868.
- Callaway, Brantly and Pedro HC Sant’Anna**, “Difference-in-differences with multiple time periods,” *Journal of econometrics*, 2021, *225* (2), 200–230.
- Cengiz, Doruk, Arindrajit Dube, Attila Lindner, and Ben Zipperer**, “The effect of minimum wages on low-wage jobs,” *Quarterly Journal of Economics*, 2019, *134* (3), 1405–1454.
- Chen, Xi and William D Nordhaus**, “Using luminosity data as a proxy for economic statistics,” *Proceedings of the National Academy of Sciences*, 2011, *108* (21), 8589–8594.
- Clemens, Michael A, Steven Radelet, Rikhil R Bhavnani, and Samuel Bazzi**, “Counting chickens when they hatch: Timing and the effects of aid on growth,” *The Economic Journal*, 2012, *122* (561), 590–617.

- Diamond, Rebecca**, “The determinants and welfare implications of US workers’ diverging location choices by skill: 1980–2000,” *American economic review*, 2016, 106 (3), 479–524.
- Donaldson, Dave and Adam Storeygard**, “The view from above: Applications of satellite data in economics,” *Journal of Economic Perspectives*, 2016, 30 (4), 171–198.
- Dreher, Axel and Steffen Lohmann**, “Aid and growth at the regional level,” *Oxford Review of Economic Policy*, 2015, 31 (3-4), 420–446.
- , **Andreas Fuchs, Bradley Parks, Austin Strange, and Michael J Tierney**, “Aid, China, and growth: Evidence from a new global development finance dataset,” *American Economic Journal: Economic Policy*, 2021, 13 (2), 135–174.
- , —, **Roland Hodler, Bradley C. Parks, Paul A. Raschky, and Michael J. Tierney**, “African leaders and the geography of China’s foreign assistance,” *Journal of Development Economics*, 2019, 140, 44–71.
- , —, —, **Bradley C Parks, Paul A Raschky, and Michael J Tierney**, “Is favoritism a threat to Chinese aid effectiveness? A subnational analysis of Chinese development projects,” *World Development*, 2021, 139, 105291.
- Galiani, Sebastian, Stephen Knack, Lixin Colin Xu, and Ben Zou**, “The effect of aid on growth: Evidence from a quasi-experiment,” *Journal of Economic Growth*, 2017, 22 (1), 1–33.
- Goodman-Bacon, Andrew**, “Difference-in-differences with variation in treatment timing,” *Journal of econometrics*, 2021, 225 (2), 254–277.
- Goodman, Seth, Sheng Zhang, Ammar A Malik, Bradley C Parks, and Jacob Hall**, “AidData’s Geospatial Global Chinese Development Finance Dataset,” *Scientific Data*, 2024, 11 (1), 529.
- Harari, Mariaflavia**, “Cities in bad shape: Urban geometry in India,” *American Economic Review*, 2020, 110 (8), 2377–2421.
- **and Maisy Wong**, “Colonial legacy and land market formality,” *Journal of Urban Economics*, 2025, 149, 103789.
- Henderson, J Vernon, Adam Storeygard, and David N Weil**, “Measuring economic growth from outer space,” *American economic review*, 2012, 102 (2), 994–1028.
- , **Tanner Regan, and Anthony J Venables**, “Building the city: from slums to a modern metropolis,” *The Review of Economic Studies*, 2021, 88 (3), 1157–1192.
- Jedwab, Remi, Luc Christiaensen, and Michael Gindelsky**, “Demography, Urbanization and Development: Rural Push, Urban Pull and ... Urban Push?,” *Journal of Urban Economics*, 2017, 98, 6–16.
- Lian, Hongping and Raul P. Lejano**, “Urbanization, Informal Sector, and Development,” *Journal of Development Economics*, 2007, 84 (1), 76–103.
- Lindlacher, Valentin and Gustav Pirich**, “The Impact of China’s “Stadium Diplomacy” on Local Economic Development in Sub-Saharan Africa,” CESifo Working Paper 10893, CESifo 2024.
- **and —**, “The Impact of China’s “Stadium Diplomacy” on Local Economic Development in Sub-Saharan Africa,” *World Development*, 2025, 185, 106765.
- Martorano, Bruno, Laura Metzger, and Marco Sanfilippo**, “Chinese development assistance and household welfare in sub-Saharan Africa,” *World Development*, 2020, 129, 104909.
- Marx, Benjamin, Thomas Stoker, and Tavneet Suri**, “The Economics of Slums in the Developing World,” *Journal of Economic Perspectives*, 2013, 27 (4), 187–210.
- Nunn, Nathan and Diego Puga**, “Ruggedness: The blessing of bad geography in Africa,” *Review of Economics and Statistics*, 2012, 94 (1), 20–36.
- OECD**, “Preliminary official development assistance levels in 2024,” [https://one.oecd.org/document/DCD\(2025\)6/en/pdf](https://one.oecd.org/document/DCD(2025)6/en/pdf), 2025.

- Pesaresi, Martino and Panagiotis Politis**, “GHS-BUILT-S R2023A - GHS built-up surface grid, derived from Sentinel2 composite and Landsat, multitemporal (1975-2030) [Dataset],” *European Commission, Joint Research Centre (JRC)*, 2023.
- **and —**, “GHS-BUILT-V R2023A - GHS built-up volume grids derived from joint assessment of Sentinel2, Landsat, and global DEM data, multitemporal (1975-2030) [Dataset],” *European Commission, Joint Research Centre (JRC)*, 2023.
- **, Marcello Schiavina, Panagiotis Politis, Sergio Freire, Katarzyna Krasnodębska, Johannes H. Uhl, Alessandra Carioli, Christina Corbane, Lewis Dijkstra, Pietro Florio, Hannah K. Friedrich, Jing Gao, Stefan Leyk, Linlin Lu, Luca Maffenini, Ines Mari-Rivero, Michele Melchiorri, Vasileios Syrris, Jamon Van den Hoek, and Thomas Kemper**, “Advances on the Global Human Settlement Layer by Joint Assessment of Earth Observation and Population Survey Data,” *International Journal of Digital Earth*, 2024, 17 (1), e2390454. Published online 30 Aug 2024.
- Qian, Nancy**, “Making Progress on Foreign Aid,” in Philippe Aghion and Steven N. Durlauf, eds., *Handbook of Economic Growth*, Vol. 2B, Elsevier, 2015, pp. 1183–1239.
- Rajan, Raghuram G. and Arvind Subramanian**, “Aid and Growth: What Does the Cross-Country Evidence Really Show?,” *Review of Economics and Statistics*, 2008, 90 (4), 643–665.
- Saiz, Albert**, “The geographic determinants of housing supply,” *The Quarterly Journal of Economics*, 2010, 125 (3), 1253–1296.
- Storeygard, Adam**, “Farther on Down the Road: Transport Costs, Trade and Urban Growth in Sub-Saharan Africa,” *The Review of Economic Studies*, 2016, 83 (3), 1263–1295.
- Sun, Liyang and Sarah Abraham**, “Estimating dynamic treatment effects in event studies with heterogeneous treatment effects,” *Journal of econometrics*, 2021, 225 (2), 175–199.
- UN DESA**, “World Population Prospects 2018: Highlights,” <https://population.un.org/wup/assets/WUP2018-Highlights.pdf>, 2019.
- **, “World Population Prospects 2024: Summary of Results,”** https://population.un.org/wpp/assets/Files/WPP2024_Summary-of-Results.pdf, 2024.
- World Bank**, “Evaluation of the Urban Community Driven Development Program,” 2012. Accessed: April 23, 2025.

**Internet Appendix to
“Foreign Aid Shapes Local Urban Development”**

VINICIOS P. SANT’ANNA
Cal Poly & MIT

CIHANG WANG
University of Illinois at Urbana-Champaign

Appendix A Descriptive Statistics

Table A.1. Summary Statistics

Variable	Observations	Mean	SD	Min	Max
Panel A - Project level information					
Project radius	1,643	100.164	105.470	1.037	499.987
Project Area	1,643	66,444.66	123,791.5	3.379	785,358
Value amount in Million of US\$ (2021 terms)	818	57.049	152.495	0	1,568.860
Panel B - Grid level information					
Distance to project (Meters)	14,536,465	1,333.461	471.423	1.241	1,999.992
Built surface (Square Meters)	14,536,465	1,904.056	2,113.167	0	10,000
Residential Built surface (Square Meters)	14,536,465	1,795.902	2,040.445	0	8,969
Non-Residential Built surface (Square Meters)	14,536,465	108.154	586.926	0	10,000
Built volume (Cubic Meters)	14,536,465	17,455.310	22,105.020	0	401,208
Residential Built volume (Cubic Meters)	14,536,465	16,252.070	20,606.190	0	401,208
Non-Residential Built volume (Cubic Meters)	14,536,465	1,203.247	7,193.571	0	251,411
Panel C - Region information (5 years before treatment)					
Total Built Surface (Millions of Square Meters)	1,643	2.500	1.780	0	8.385
Median Grid Built Surface (Square Meters)	1,643	1,859.550	1,757.431	0	7,338
Built Surface Growth Rate (%)	1,643	11.097	24.508	-8.389	452.899
Total Built Volume (Millions of Cubic Meters)	1,643	22.866	18.360	0	91.874
Median Grid Built Volume (Cubic Meters)	1,643	15,964.070	16,453.790	0	64,104
Built Volume Growth Rate (%)	1,643	10.742	24.602	-8.453	452.761

Notes: This table reports the summary statistics for the main variables used in the analysis. Panel A summarizes the project-level characteristics, including the radius of the aid projects' footprints and the amount of investment in 2021 dollar terms. Panel B reports the grid-level information for the sample of 100-meter cells used in the analysis. This includes the distance from each grid to the project center, the built surface in square meters, and volume in cubic meters by residential and non-residential types. Panel C describes the information on the regions of each project measured at the baseline period, 5 years prior to treatment. These are calculated as aggregated measures for the 2-kilometer area around the project location, and include the total, median, and growth rate in built surface and volume. This is also the information we use to perform the heterogeneity analysis.

Table A.2. Built Environment and Project Allocation: Cross-Sectional Evidence

	Dependent Variable: Project Amount (2021 USD)			
	Median Surface (1)	Median Volume (2)	Mean Volume (3)	Mean Surface (4)
Pre-treatment Built Environment	-9126.62** (3476.10)	-903.57** (379.11)	-1000.14** (443.52)	-11809.94*** (4429.84)
Project Area (sq. km)	36.96 (39.67)	38.29 (39.74)	36.73 (40.00)	33.40 (39.92)
Observations	816	816	816	816
R-squared	0.271	0.270	0.269	0.271
Adj. R-squared	0.202	0.201	0.200	0.203
Within R-sq.	0.012	0.010	0.010	0.012

Notes: Each column presents results from a cross-sectional linear regression estimating the relationship between pre-project built environment (median/mean surface or volume for the entire microregion) and project expenditure allocation in 2021 dollar terms. In this analysis, we also include the project size (in square kilometers) as a control variable. All regressions include fixed effects for country, project type, and commitment year. Robust standard errors are in parentheses. Statistical significance: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

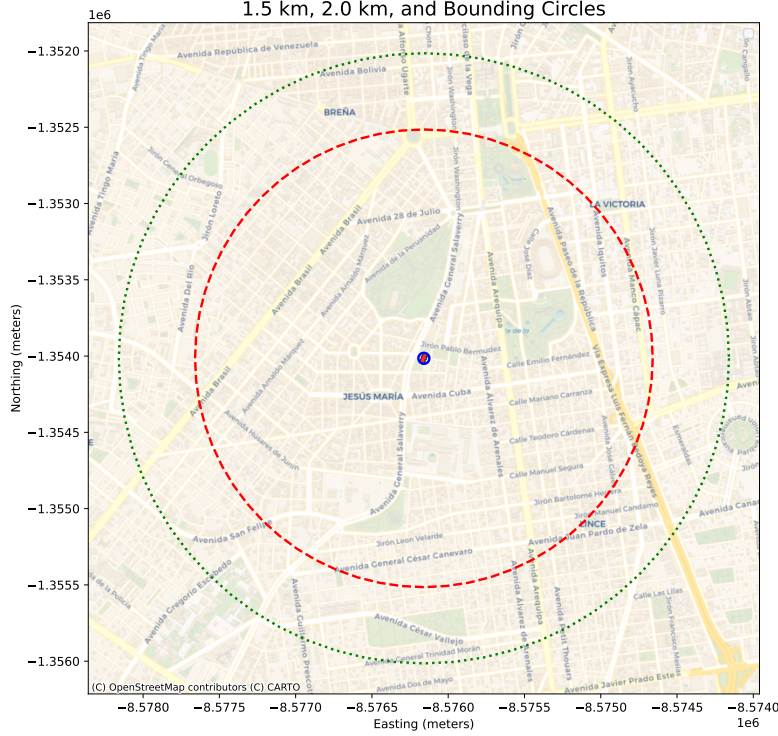


Figure A.1. Illustration of the Identification Strategy. This figure illustrates the identification strategy discussed in Section 3.2. As we describe in Eq. (3), we define a spatial threshold (in this example, $\theta = 1.5\text{km}$) and consider all grids located within a distance $\theta = 1.5\text{km}$ (red circle) from the project as treated, while those located at a distance greater than $\theta 1.5\text{km}$ but smaller than 2km (green circle) are defined as our control units.

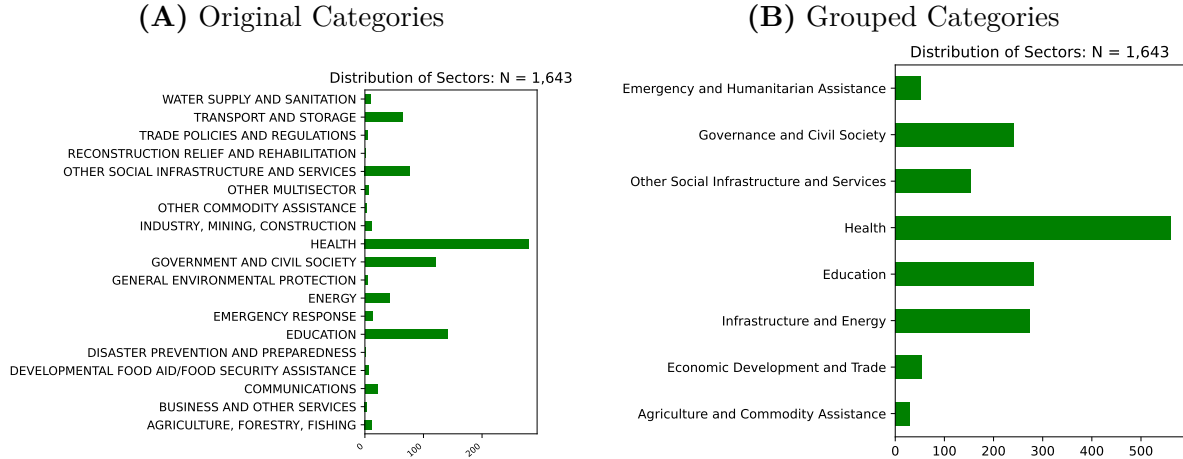


Figure A.2. Type Distribution of Aid Projects. This figure shows the counts of different types of projects in Africa between 2000 and 2021. Panel A is the definition of projects in the original Aid Dataset (Goodman et al., 2024), and in Panel B, we group related types of projects into eight different categories: (i) Agriculture and Commodity Assistance, (ii) Economic Development and Trade, (iii) Infrastructure and Energy, (iv) Education, (v) Health, (vi) Other Social Infrastructure and Services, (vii) Governance and Civil Society, (viii) Emergency and Humanitarian Assistance. We adopt this reclassification mostly to avoid issues with small sample sizes for certain types of projects when performing heterogeneity analysis by type.

Appendix B Alternative Threshold Designs

In the main text, [Figure 3](#) presents the event study estimates when using $\theta = 1.5\text{km}$ as the threshold to define treated and control units. One concern is that our results may be sensitive to the choice of this threshold. In this section, we replicate the event study specification from Equation (4) for built surface and volume using different spatial thresholds (θ) to define treatment exposure: 1km, 1.25km, 1.5km, and a “donut” design that excludes a buffer region between treatment and control areas. [Figure B.1](#) presents the results for built surface and [Figure B.2](#) the results for built volume. Across all specifications, we observe consistent post-treatment increases in built surface and volume. Most importantly, we find negligible and statistically insignificant effects in the pre-treatment periods, supporting our identification strategy, regardless of the choice of treatment definition.

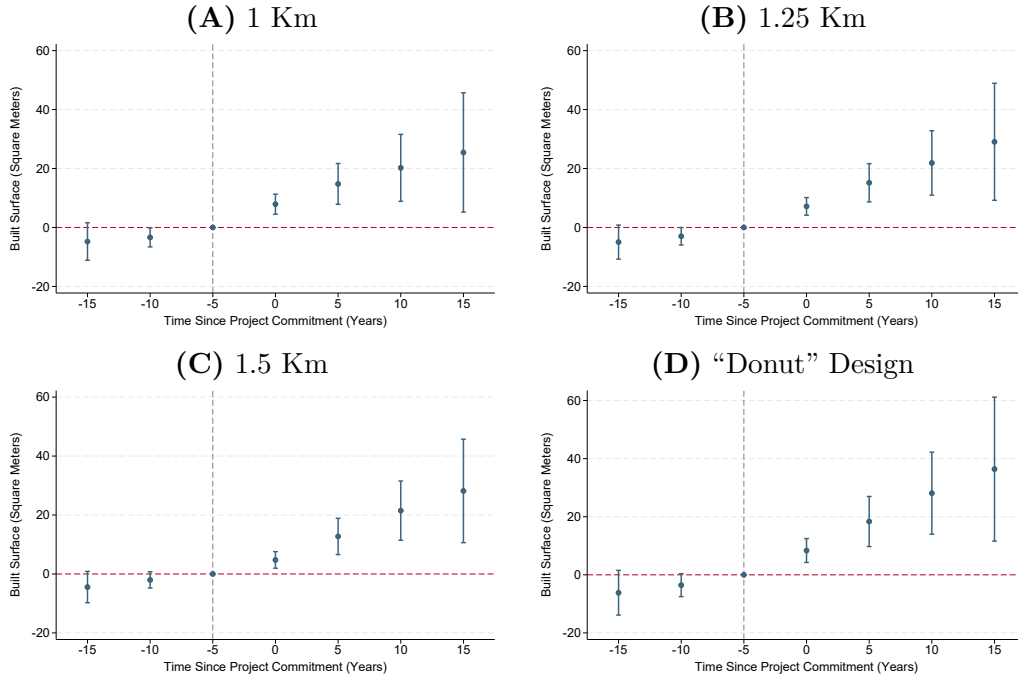


Figure B.1. Event Study under alternative threshold designs: Built Surface. This figure plots the estimated coefficients and 95% confidence intervals for the event study specification using (A) 1km, (B) 1.25km, (C) 1.5km as the treatment cut-off and the (D) “donut” design corresponding to the specification in equation (4).

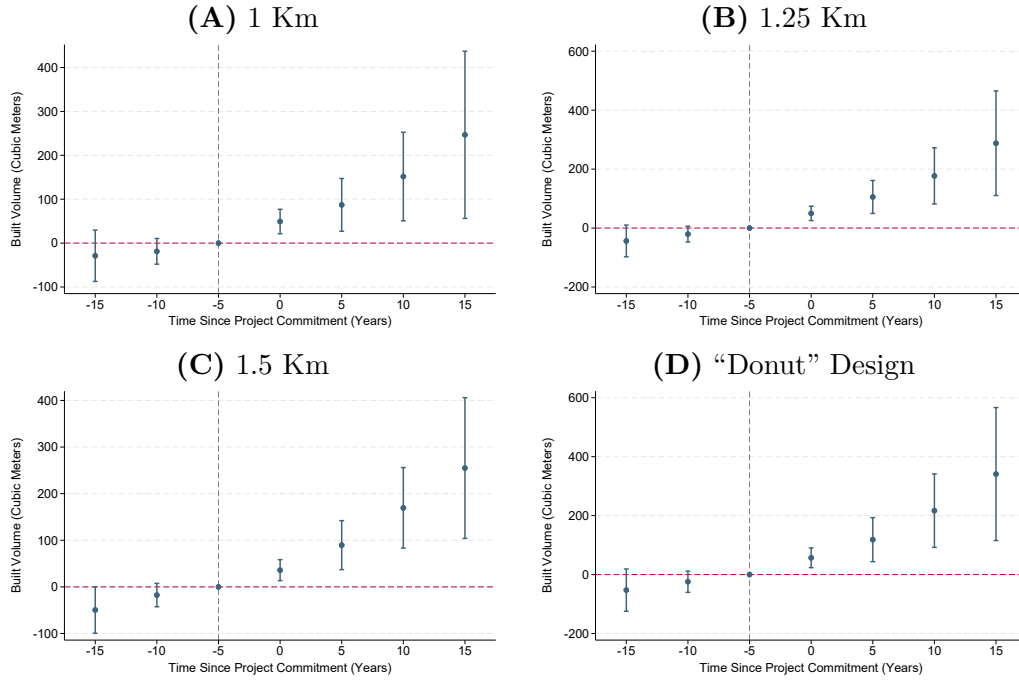


Figure B.2. Event Study under alternative threshold designs: Built Volume. This figure plots the estimated coefficients and 95% confidence intervals for the event study specification using (A) 1km, (B) 1.25km, (C) 1.5km as the treatment cut-off and the (D) "donut" design corresponding to the specification in equation (4).

Appendix C Additional Results

In this section, we explore additional results about the heterogeneity and robustness of our findings in the main text. We conduct two exercises to further examine the effects of foreign aid on local urbanization patterns. First, we investigate whether foreign aid affects building height in addition to the surface area and volume measures analyzed in the main text. Because built volume is, by definition, influenced by changes in the built area, this helps us better distinguish between the extensive margin (more building) and the intensive margin (taller buildings) effects. Second, we further examine the heterogeneity of our findings. Recent studies in causal inference have emphasized that average treatment effects can obscure heterogeneity, potentially masking both highly effective interventions and ineffective or even harmful ones (Athey and Imbens, 2017). To examine this in our context, we test the heterogeneity of our estimates across project types to identify which categories of aid interventions may generate the strongest urban development responses.

C.1 The Effects of Foreign Aid on Buildings Height

We begin by assessing the effects of foreign aid on the average built height. We divide our measure of built volume by the built area, which gives us an estimate for the average built height of a grid. We then use this measure of height as dependent variable and estimate the distance gradients (Eq. (1)) and average treatment effects (Eq. (3)). Figure C.1 shows that both in terms of the distance gradient (Panel A) and the event study design (Panel B) we do find that foreign aid significantly increases building density, as measured by average building height. While the estimated magnitudes are modest in absolute terms, these effects are statistically significant and economically meaningful.

These height increases represent intensive margin effects that complement the extensive margin expansion documented in built surface area. Therefore, our findings for built volume are not merely reflecting the expansions in surface built up, but also in density. The simultaneous growth in both surface area and building height indicates that aid projects generate comprehensive urban densification, with more intensive land use patterns in areas closer to projects. Moreover, when aggregated across the treatment area, these incremental height increases translate to more meaningful increases in total built volume per unit of land, suggesting that aid projects create economic incentives for more efficient land utilization. Figure C.2 also shows that our findings are also robust to the choice of the treatment threshold.

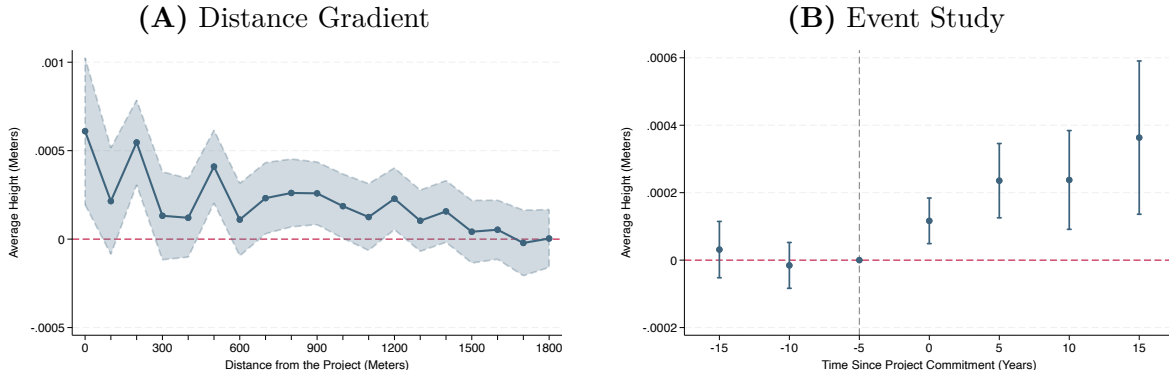


Figure C.1. Effects on Height. Panel A plots the estimated coefficients of distance dummies for every 100 meters away from the center of the project location and 95% confidence intervals according to the specification in equation (1). Panel B plots the estimated coefficients and 95% confidence intervals for the event study specification using 1.5km as the treatment cut-off corresponding to the specification in equation (4). Dependent variable is the average building height in meters, and it is calculated by the volume divided by the built surface of a grid.

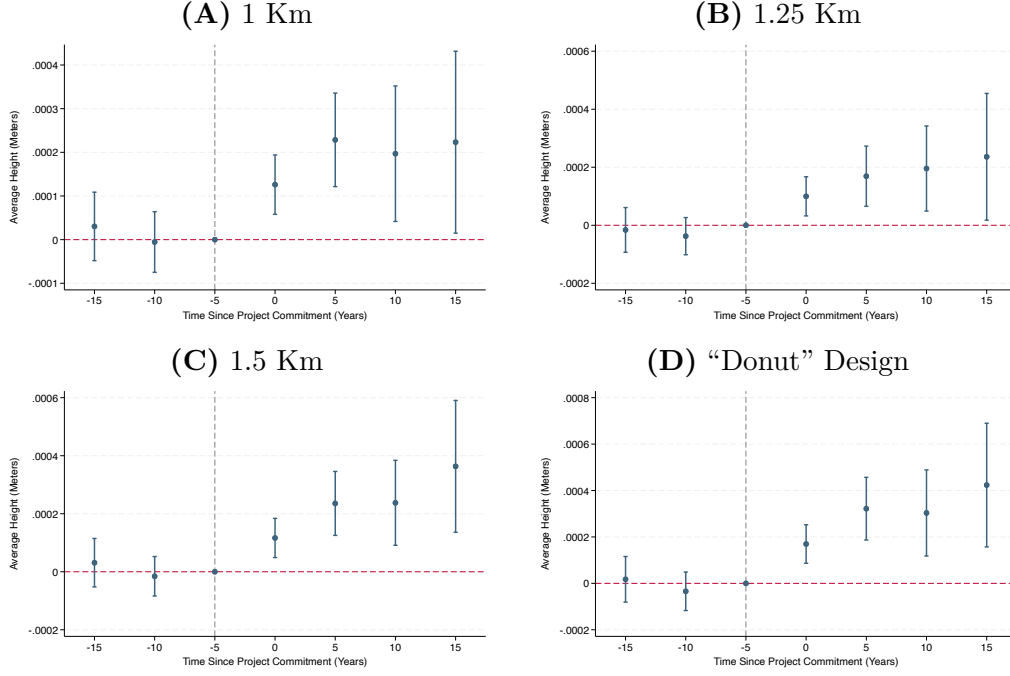


Figure C.2. Event Study Specification under alternative threshold designs: Height. This figure plots the estimated coefficients and 95% confidence intervals for the event study specification using 1km, 12.5km, 1.5km as the treatment cut-off and the “donut” design corresponding to the specification in equation (4) for each type of project separately. The coefficients is the difference between height within and beyond the treatment threshold surrounding the project location from 15 years before to 15 years after the establishment year of the project.

C.2 Heterogeneity by Project Type

In this section, we assess the heterogeneity of our main estimates for different project types. Following the project categories from Panel B of [Figure A.2](#), we estimate [eq. \(1\)](#) separately, restricting the sample to each project type. Although sample sizes vary considerably across types, this analysis provides valuable insights into identifying which project categories are most effective in shaping local urbanization patterns.

Table C.1. Distance to Aid Projects and Urbanization by Type.

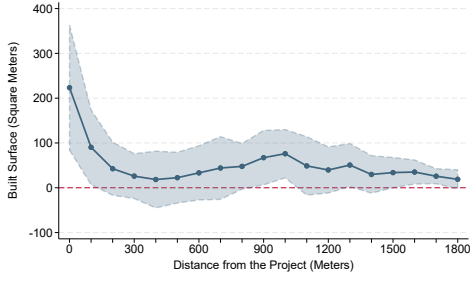
Panel A. Built Volume								
	Agriculture and Commodity Assistance (1)	Economic Development and Trade (2)	Infrastructure and Energy (3)	Education (4)	Health (5)	Social Infrastructure and Services (6)	Government and Civil Society (7)	Emergency and Humanitarian Assistance (8)
Distance \times Post	-0.023 (0.017)	-0.079*** (0.023)	-0.022** (0.009)	-0.034** (0.015)	-0.028*** (0.008)	-0.032* (0.018)	0.006 (0.010)	0.037** (0.016)
Observations	255,356	464,394	2,393,698	2,470,208	4,931,933	1,357,041	2,137,064	449,930
Units	36,484	66,413	342,081	353,034	704,819	193,950	305,540	64,299
Periods	7	7	7	7	7	7	7	7
Clusters	29	53	273	281	560	154	242	51
R-squared	0.98	0.96	0.98	0.97	0.97	0.97	0.98	0.96

Panel B. Built Surface								
	Agriculture and Commodity Assistance (1)	Economic Development and Trade (2)	Infrastructure and Energy (3)	Education (4)	Health (5)	Social Infrastructure and Services (6)	Government and Civil Society (7)	Emergency and Humanitarian Assistance (8)
Distance \times Post	0.016 (0.172)	-0.721*** (0.207)	-0.135 (0.083)	-0.170 (0.147)	-0.226*** (0.064)	-0.210 (0.154)	0.072 (0.109)	0.086 (0.126)
Observations	255,356	464,394	2,393,698	2,470,208	4,931,933	1,357,041	2,137,064	449,930
Units	36,484	66,413	342,081	353,034	704,819	193,950	305,540	64,299
Periods	7	7	7	7	7	7	7	7
Clusters	29	53	273	281	560	154	242	51
R-squared	0.98	0.98	0.98	0.97	0.98	0.98	0.99	0.97

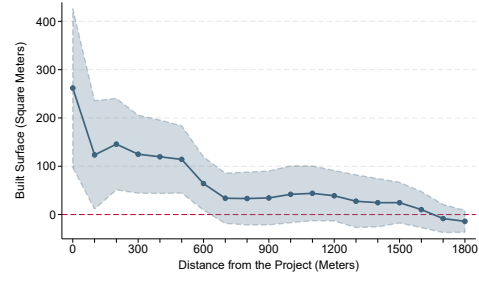
Notes: This table presents the effects on the urbanization of grids based on the distance to foreign aid projects according to the specification in [equation \(2\)](#). The dependent variable is the built surface in Panel A and the built volume in Panel B. Column (1) shows the estimate for the full sample of projects, while columns (2) to (8) estimate the same specifications for each project type separately. The estimated coefficient is interpreted as the associated decrease in square meters of built surface or cubic meters of built volume with a one-meter distance away from the project location center. Robust standard errors clustered at the level of projects are in parentheses. Statistical significance: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

[Table C.1](#) shows the estimated coefficient for the interaction term of *distance* \times *post* corresponding to [eq. \(2\)](#). Panel A uses the built surface as the dependent variable, while Panel B uses built volume. We find that projects classified as *economic development and trade* exhibit the steepest distance gradients, indicating highly localized urban development responses. *Health* and *education* projects also generate significant spatial concentration effects, though smaller in magnitude, and closer to the average effects shown in [Table 1](#). In contrast, *emergency and humanitarian assistance* projects show positive distance gradients, likely reflecting their deployment in areas experiencing disasters or economic distress. [Figures C.3](#) and [C.4](#) illustrate these heterogeneous patterns.

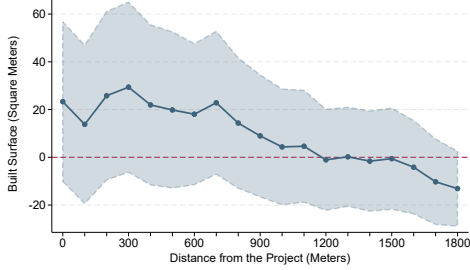
(A) Agriculture and Commodity Assistance



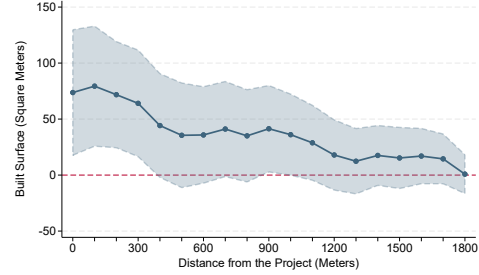
(B) Economic Development and Trade



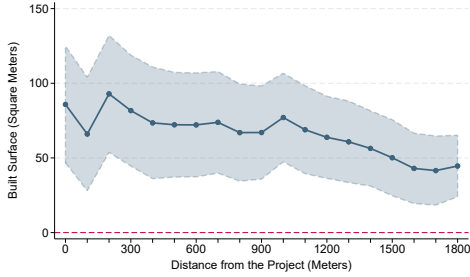
(C) Infrastructure and Energy



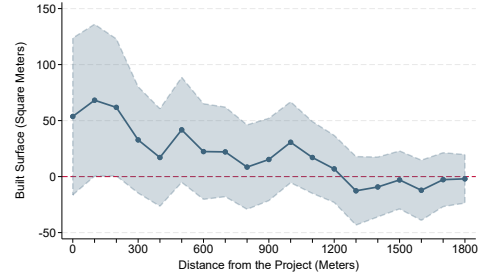
(D) Education



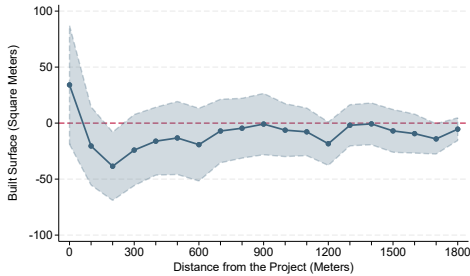
(E) Health



(F) Social Infrastructure and Services



(G) Government and Civil Society



(H) Emergency and Humanitarian Assistance

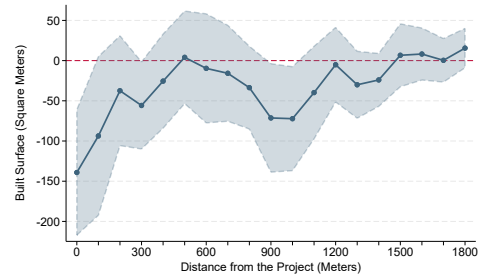
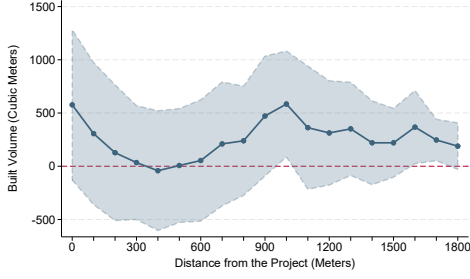


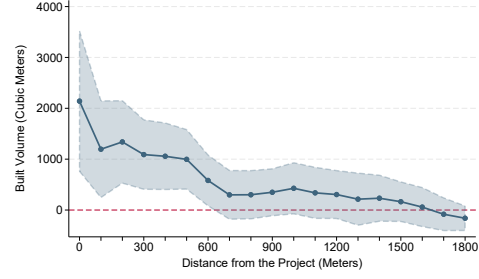
Figure C.3. Distance Gradient by Project Type: Built Surface. This figure plots the estimated coefficients of distance dummies for every 100 meters away from the center of the project location and 95% confidence intervals according to the specification in equation (1). We estimate the specification of the built surface for each type of projects from Panel (A) to Panel (H).

Figure C.5 and Figure C.6 display the evolution of built surface and volume using event study difference-in-differences estimation by different project types. We find that our identification strategy is robust across project types, with most sectors exhibiting no differential pre-treatment trends between areas closer to and farther from project sites. The only project category that shows some evidence of potential pre-trends is projects associated with *health* interventions, which may reflect strategic placement of health-related aid projects within microregions.

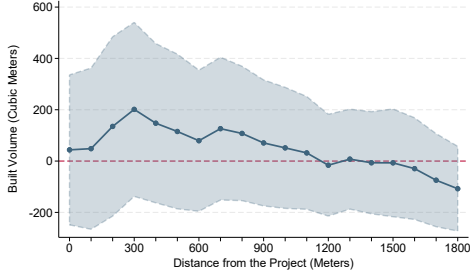
(A) Agriculture and Commodity Assistance



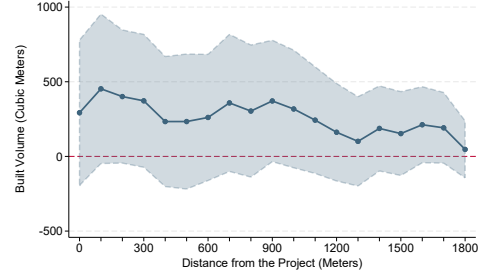
(B) Economic Development and Trade



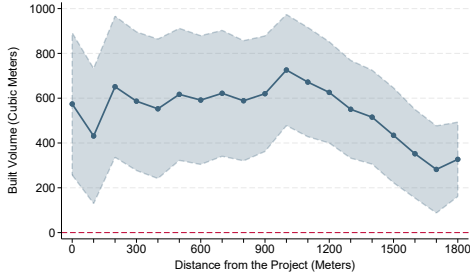
(C) Infrastructure and Energy



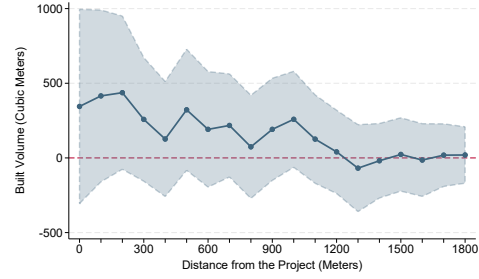
(D) Education



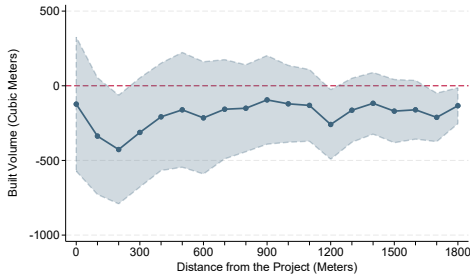
(E) Health



(F) Social Infrastructure and Services



(G) Government and Civil Society



(H) Emergency and Humanitarian Assistance

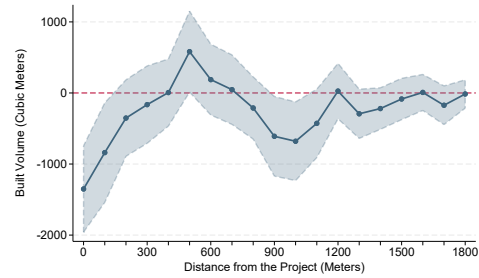


Figure C.4. Distance Gradient by Project Type: Built Volume. This figure plots the estimated coefficients of distance dummies for every 100 meters away from the center of the project location and 95% confidence intervals according to the specification in equation (1). We estimate the specification of the built volume for each project type from Panel (A) to Panel (H).

Future research evaluating the causal impacts of health-related foreign aid should carefully account for these potential pre-treatment trend violations when designing identification strategies. For projects classified as *economic development and trade* or *social infrastructure and services*, we find substantial responses in built surface and volume.

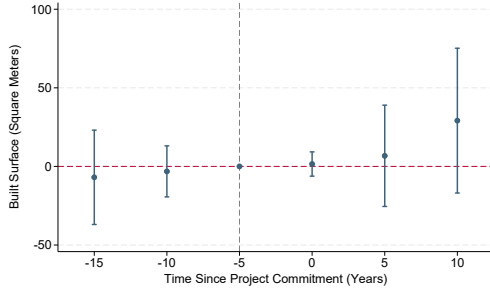
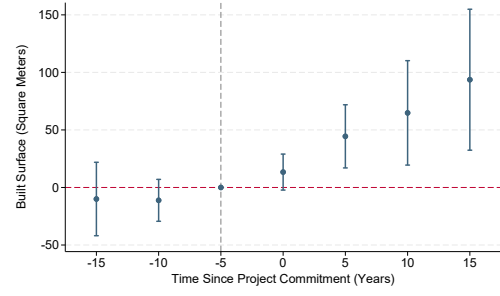
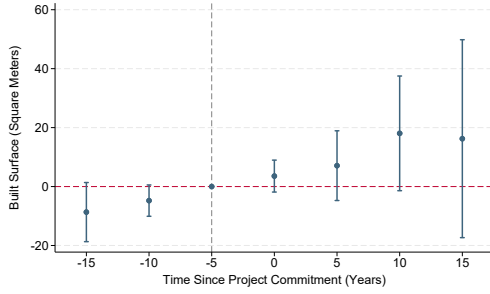
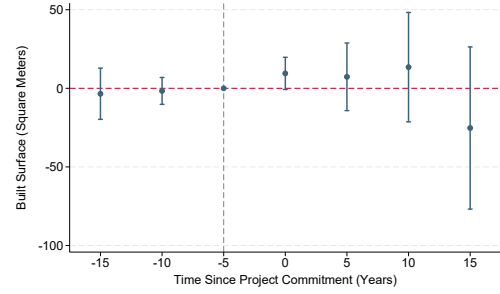
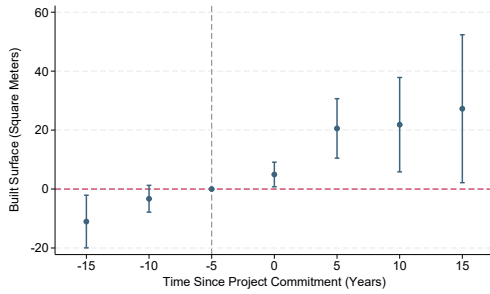
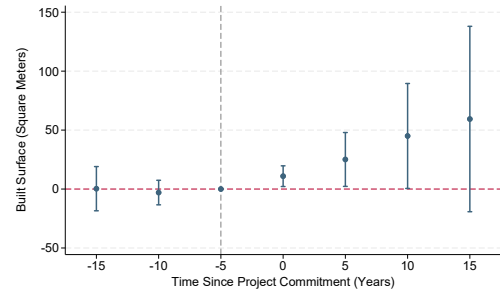
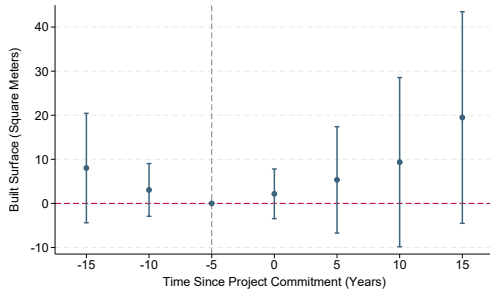
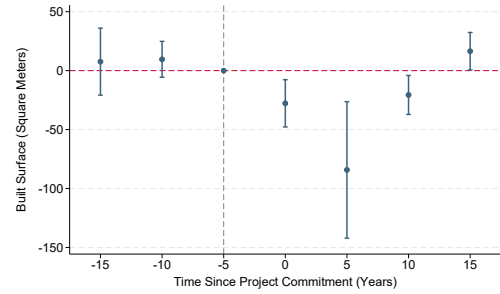
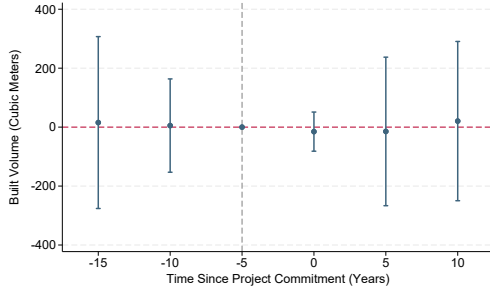
(A) Agriculture and Commodity Assistance**(B) Economic Development and Trade****(C) Infrastructure and Energy****(D) Education****(E) Health****(F) Social Infrastructure and Services****(G) Government and Civil Society****(H) Emergency and Humanitarian Assistance**

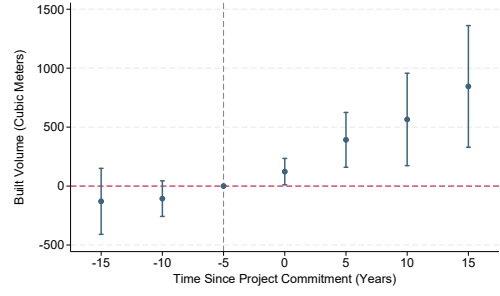
Figure C.5. Event Study by Project Type: Built Surface. This figure plots the estimated coefficients and 95% confidence intervals for the event study specification using 1.5km as the treatment cut-off corresponding to the specification in equation (4) for each type of project separately.

Projects in *infrastructure and energy*, as well as *health*, also generate positive statistically significant results, though somewhat smaller in magnitude. *Agriculture and commodity assistance*, *education*, and *government and civil society* types show weaker post-treatment responses, and statistically insignificant coefficients. In contrast, *emergency and humanitarian assistance* decreases built surface and volume, consistent with their deployment in areas experiencing disasters or population displacement.

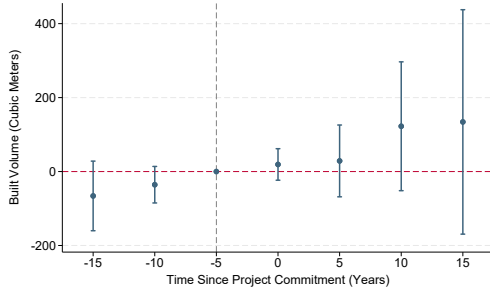
(A) Agriculture and Commodity Assistance



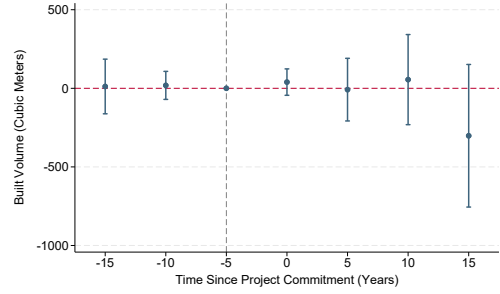
(B) Economic Development and Trade



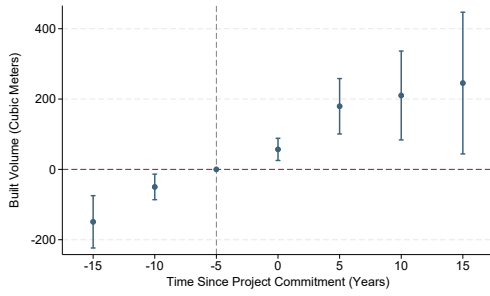
(C) Infrastructure and Energy



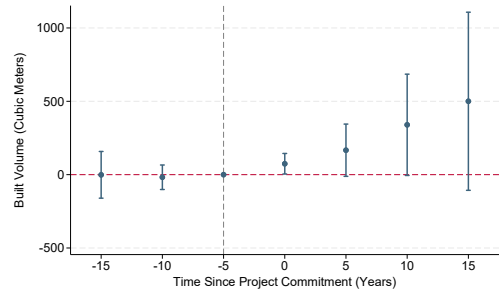
(D) Education



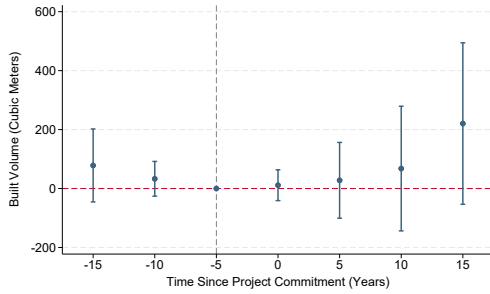
(E) Health



(F) Social Infrastructure and Services



(G) Government and Civil Society



(H) Emergency and Humanitarian Assistance

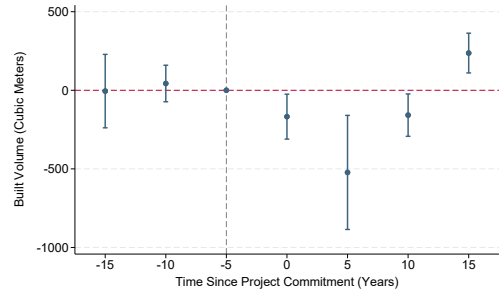


Figure C.6. Event Study by Project Type: Built Volume. This figure plots the estimated coefficients and 95% confidence intervals for the event study specification using 1.5km as the treatment cut-off corresponding to the specification in equation (4) for each type of project separately.