# Foreign Aid Shapes Local Urban Development*

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**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-up surface and volume at 100-meter grid cells within a 2-kilometer 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.

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# 1 Introduction

Sub-Saharan Africa is among 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 region's rapid urbanization.

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 not addressed its role in shaping micro-level urban development patterns. This reflects, in part, the challenges of 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 arising from selection into aid project locations. 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 highly detailed micro-level satellite-based urban structure data to implement a within-microregion empirical strategy. We define a microregion as the grid cells within 2 kilometers (approximately 1.24 miles) of projects and compare the grids closer to the aid projects with 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 endogeneity concerns 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 significantly increases local urban development. Areas closer to aid projects exhibit significantly higher surface and volume of urban development, with the effects declining sharply with distance and becoming statistically insignificant beyond approximately 1.5 - 1.7 kilometers (0.93 - 1.06 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 per 100-meter grid.

Using binary treatment definitions, we deploy a spatial ring design that defines concentric treatment and control areas, comparing grids within an inner ring around each project to those in an outer ring within the same microregion. To further mitigate concerns about spillovers or other indirect spatial effects from treated to control units, we exclude the intermediate areas separating the two rings from the sample. Testing alternative ring designs, we consistently find that grids closer to aid projects experience increases of 17–36 square meters in built surface and 145–263 cubic meters in built volume, on average. 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 into 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 away. 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 identification assumption that project location within microregions is plausibly exogenous conditional on a demanding set of fixed effects. Following aid implementation, treatment effects emerge sharply and grow steadily over time, reaching approximately 50 square meters of additional built-up surface and over 400 cubic meters of additional built-up volume after 15 years on average per grid. 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 heterogeneity in our results, we find that these effects are overwhelmingly driven by residential development, suggesting that aid projects are likely 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). Finally, we also test for heterogeneity by the project amount in dollars. While point estimates suggest that larger projects may lead to greater urbanization, the results are not robust in terms of statistical significance, preventing us from drawing strong conclusions about the role of project scale.

**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, researchers have often 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 prevalent in this 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; Combes et al., 2025). A growing number of studies have 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

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

education and reduce child mortality (Martorano et al., 2020), our findings suggest that foreign aid projects may also affect the local provision of amenities that make locations near the projects more attractive to residents, leading to a permanent shift in local urbanization patterns.

## 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.[2] 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 with 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 comprises 1,643 aid projects across 44 countries, totaling over $46 billion (in USD 2021 terms) 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 100-meter radius and is associated with an investment of US$57 million. A typical project in our sample can be either a school, a hospital, or an industrial park.[3]

**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.[4] The dataset spans the period from 1975 to 2020, with snapshots every five years, and offers a spatial resolution of 100-meter (328 feet)

[2]Although we refer to this information as "aid" for brevity (following the dataset name), AidData codes them as *official finance* that spans multiple flow classes, including "ODA-like" (Official Development Assistance) and "OOF-like" (Other Official Flows), and, in some cases, "Vague Official Finance" when information is insufficient for classification. In AidData's *Tracking Underreported Financial Flows* (TUFF) framework, OOF-like flows are official-sector transactions that do not meet OECD-DAC criteria for official development assistance (ODA) (AidData, 2017, 2021; OECD, 2023).

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

[4]Sentinel-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.

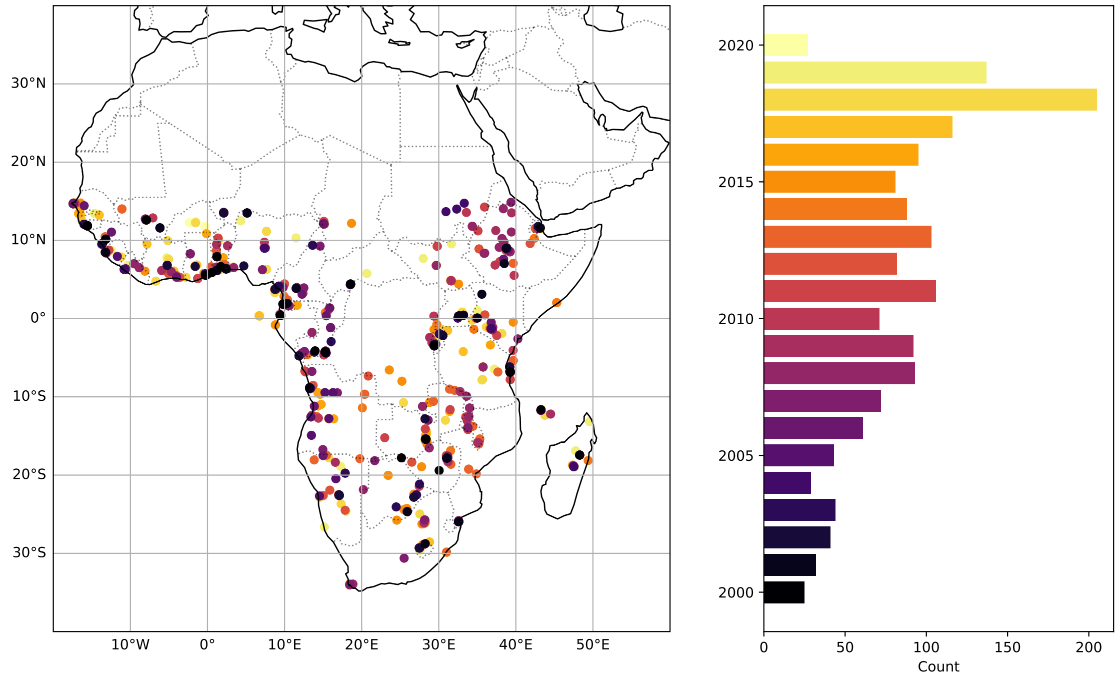


**Figure 1. Space and Time distributions of Aid Projects**. This figure illustrates the geographic distribution of the development projects in Africa between 2000 and 2020 (on the left) and the distribution by commitment year (on the right). The colors represent the commitment year of projects, with 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.

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.[5] 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.[6]

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-

[5]Non-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.

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

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 GSHL R2023 also excels in 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 the project's location choice. Previous research shows that foreign aid to a country or region is often 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 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 that use nighttime light datasets, which typically span grids ranging from 30 to 50 kilometers. We later provide evidence supporting 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).

In addition to endogenous project placement, our setting also raises a second challenge specific to spatial causal inference: spatial interference between treated and control units. Interference implies that untreated grids can be affected by nearby treatment through migration, market access, and other local general-equilibrium adjustments. As a result, grids differ in their exposure to treatment, and treated and untreated grids rarely share the same level of exposure. In this context, Butts (2024) shows that the "switching effect" (the effect of toggling a grid's own treatment while fixing its exposure to other grids' treatment) is generally not identified under a difference-in-differences design because it would require the treated and untreated grids share the same level of exposure.[7] Accordingly, we follow Butts (2023, 2024) and target the total effect of aid projects on the treated grids, which allows exposure to adjust endogenously and thereby incorporates the project's direct effect and any local spillover effects.

### 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:

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

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.[8] We opt to use the commitment date as the treatment period because it represents the 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 project's actual start date 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 $t$. $\alpha_{ri}$ is a vector of microregion-by-grid-specific binary variables. This set of dummy variables 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). $\alpha_{rt}$ 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

[7]Following Butts (2024), let potential outcomes depend on own treatment $D_i$ and an exposure mapping $h_i(D)$. The *switching effect* is $Y_i(1, h) - Y_i(0, h)$, which changes only $i$'s treatment status while holding exposure fixed at $h$. The *total effect* is $Y_i(1, h_i(D)) - Y_i(0, 0)$, which compares the observed treatment regime (including induced exposure) to a baseline with no treatment and no exposure. Our spatial DiD with far-away controls is designed to identify the total effect under local-spillovers assumptions.

[8]The data provides the date of commitment, implementation, and completion date.

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 within the project's 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:

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

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 $\delta_D$ 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, relative to those farther away, we explore an alternative approach based on a spatial differences-in-differences design. In identifying treated and control units, a major concern is the potential indirect influence that treated units may have on nearby control units. If the treated and control units are too close, there is a concern that the treatment units may indirectly affect our estimates, biasing our treatment estimates. If they are too far apart, control units can become less comparable to treated ones in unobservable characteristics.

We address this concern by adopting a ring, or "donut," strategy: we define an inner ring around the aid projects as treated units, an outer ring sufficiently far from the treated units as control units, and exclude units between the rings from the sample. Based on the Eq. (1) estimates, we can define spatial thresholds and consider all grids located within a distance $\underline{\theta}$ from the project as treated, while those located at a distance greater than $\bar{\theta}$ are defined as control units. We employ the following specification:

$$y_{rit} = \alpha_{ri} + \alpha_{rt} + \delta_{\underline{\theta},\bar{\theta}} \cdot Treated_{ri}(\underline{\theta}, \bar{\theta}) \times Post_t + \epsilon_{rit}, \qquad with \quad \underline{\theta} \leq \bar{\theta} \tag{3}$$

where $Treated_{ri}(\underline{\theta}, \bar{\theta})$ equals one if grid $i$ is within distance $\underline{\theta}$ from the project in microregion $r$, with control units located beyond a distance of $\bar{\theta}$. $\alpha_{ri}$ and $\alpha_{rt}$ are the same set of binary variables as defined before. $\delta_{\underline{\theta},\bar{\theta}}$ captures the average treatment effect (ATT) for a given inner and outer ring definition. Determining the proper ring size is critical for the unbiased estimation of the causal effects in ring designs (Butts, 2023). As we discuss in Section 4.1, effects tend to decrease more rapidly after 1 km from projects, and grids beyond 1.5-1.7 km do not seem to experience effects. Guided by our empirical distance gradient estimates, we adopt $\underline{\theta} = 1.2$ km and $\bar{\theta} = 1.8$ km as our preferred design. We examine multiple threshold definitions for the rings to assess robustness. We also test for an alternative design when rings are contiguous (that is, when $\underline{\theta} = \bar{\theta}$).

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:

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

where $Treated_{ri,t-\tau}(\underline{\theta}, \bar{\theta})$ is an indicator variable for treatment time $\tau$. We estimate the above specification using a 15-year window before and after the aid project, with the period 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 effects of foreign aid on urbanization vary with distance from the project. Figure 2 presents the estimated coefficients $\beta_d$ 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

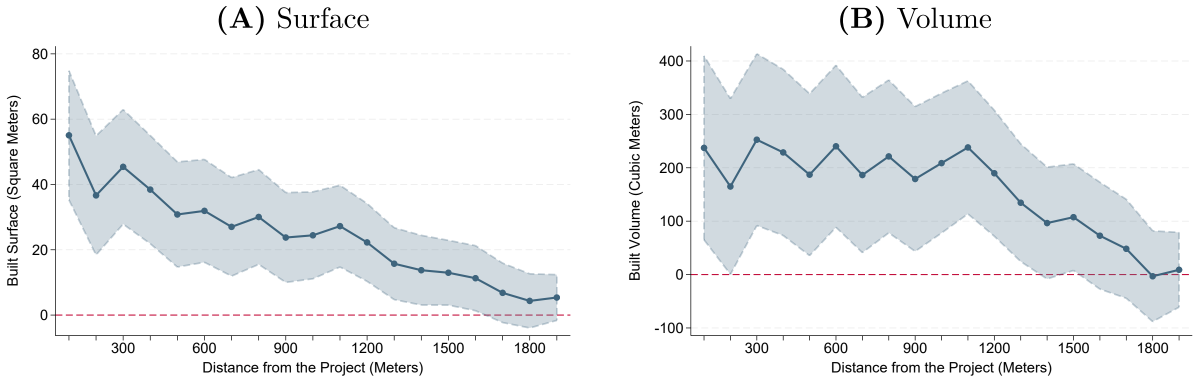


**Figure 2. Distance Gradient.** This figure plots the estimated coefficients of distance dummies for every 100 meters away from the center of the project location and 95% confidence intervals according to the specification in equation (1). Panel A shows the estimates for built-up surface in square meters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

it begins to decline more sharply.[9] Importantly, the effects become statistically insignificant beyond approximately 1.5 to 1.7 kilometers from projects, providing empirical guidance for defining treatment and control areas in our subsequent analysis.[10]

## 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 of built surface and 15.6 fewer cubic meters of built volume per grid. These estimates provide a baseline measure of the spatial decay rate of urbanization effects.

Columns (2) through (5) present results from the binary treatment specifications in Eq. (3), using alternative ring thresholds for treatment. Column (2) adopts contiguous rings at 1.5km thresholds. Columns (3)-(5) adopt an upper threshold of $\bar{\theta} = 1.8$ km, classifying control units as those beyond 1.8 km from projects, and define alternative inner ring definitions, with 1.2km, 900m, and 600m, respectively. Across all specifications, we find large and statistically significant effects on both surface and volume. The estimates range from an increase of 17 to 36 square meters in

[9] In 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.

[10] In the Online Appendix, Figure C.7 extends the area of analysis to a 2.5-kilometer radius from projects to test the robustness of our distance gradient estimates at larger distances. While this specification allows us to detect potential urbanization effects farther from project sites, grids become less comparable in unobservable characteristics as the microregion area increases. The results show patterns that are similar to Figure 2, supporting the choice of approximately 1.5–1.7 kilometers as a threshold where effects are no longer detected.

built-up surface and from 145 to 263 cubic meters in built-up volume per grid. The consistency of results across different threshold definitions suggests that our findings are robust to alternative ways of defining treatment exposure. We also observe that the smaller the inner ring is defined (as represented by a smaller $\underline{\theta}$), the larger the estimates become, consistent with the idea of higher effects in areas closer to the project. Our 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 to obtain the total expected average effects within the treated areas for each project. As Table 1 shows, the average treatment effect within a 1.2 km radius is 26 square meters of built-up surface and 222 cubic meters of built-up volume per treated grid. On average, each project has 531 treated grids under this cutoff.[11] Multiplying per-grid effects by the average number of treated grids yields an average aggregate increase of approximately 13.8 thousand square meters of built surface and over 118 thousand cubic meters of volume in the treated area relative to those beyond 1.8 kilometers away from the projects. These numbers illustrate the sizable and highly localized urban expansion driven by foreign aid projects.

Figure 3 plots the estimated coefficients on the event-time indicator using our preferred ring design strategy ($\underline{\theta} = 1.2$, $\bar{\theta} = 1.8$). Results are robust to alternative choices for the ring thresholds.[12] 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 not statistically significant, indicating that the treated and control grids followed parallel urbanization trends prior to 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 increases steadily over time. On average, built surface increases by approximately 50 square meters per grid, and built volume rises by more than 400 cubic meters per grid after 15 years of the project's implementation. These dynamics suggest that aid projects

[11] The number of treated grids varies by project due to differences in project size. According to our preferred ring design, we define a treated grid as any 100m × 100m pixel that falls within the inner ring area between the project radius and the 1.2 km buffer.

[12] Figures B.1 and B.2 show the results for the alternative ring definitions.

**Table 1. Average Effect of Aid Projects on Urbanization.**

**Panel A. Built Surface**

| | Distance (Meters) (1) | $\bar{\theta} = 1.5$ km $\underline{\theta} = 1.5$ km (2) | $\bar{\theta} = 1.8$ km $\underline{\theta} = 1.2$ km (3) | $\bar{\theta} = 1.8$ km $\underline{\theta} = 900$ m (4) | $\bar{\theta} = 1.8$ km $\underline{\theta} = 600$ m (5) |
|---|---|---|---|---|---|
| Distance × Post | –0.023*** | | | | |
| | (0.005) | | | | |
| Treated × Post | | 17.259*** | 25.973*** | 29.897*** | 35.926*** |
| | | (3.662) | (6.182) | (7.265) | (8.270) |
| Observations | 14,459,624 | 14,459,624 | 7,721,047 | 5,211,557 | 3,356,108 |
| Units | 2,066,620 | 2,066,620 | 1,103,549 | 744,884 | 479,694 |
| 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 (Meters) (1) | $\bar{\theta} = 1.5$ km $\underline{\theta} = 1.5$ km (2) | $\bar{\theta} = 1.8$ km $\underline{\theta} = 1.2$ km (3) | $\bar{\theta} = 1.8$ km $\underline{\theta} = 900$ m (4) | $\bar{\theta} = 1.8$ km $\underline{\theta} = 600$ m (5) |
|---|---|---|---|---|---|
| Distance × Post | –0.156*** | | | | |
| | (0.043) | | | | |
| Treated × Post | | 145.768*** | 222.461*** | 233.584*** | 262.731*** |
| | | (33.769) | (58.868) | (68.298) | (77.397) |
| Observations | 14,459,624 | 14,459,624 | 7,721,047 | 5,211,557 | 3,356,108 |
| Units | 2,066,620 | 2,066,620 | 1,103,549 | 744,884 | 479,694 |
| 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 the estimates of the average effects on the urbanization of grids based on the different approaches. The dependent variable is the built surface in Panel A, and the built volume in Panel B. Column (1) presents the estimates for the average effects as modulated by the distance, following Eq. (2). Columns (2)-(5) present the difference-in-differences estimates using alternative ring thresholds according to the specification in equation (3). Column (2) shows the estimates using contiguous rings with $\bar{\theta} = \underline{\theta} = 1.5$ km. Columns (3)-(5) adopt an upper threshold of $\bar{\theta} = 1.8$ km, classifying control units as those beyond 1.8 km from projects, and define alternative inner ring definitions, with 1.2km, 900m, and 600m, respectively. The coefficient is the relative effect of the foreign aid project on the urbanization of grids within the chosen inner-ring threshold compared to those in the outer-ring area. Robust standard errors clustered at the level of projects are in parentheses. Statistical significance: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

generate a persistent shift in local urbanization trajectories, with areas closer to projects urbanizing at a faster rate relative to farther areas.[13]

[13] 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.

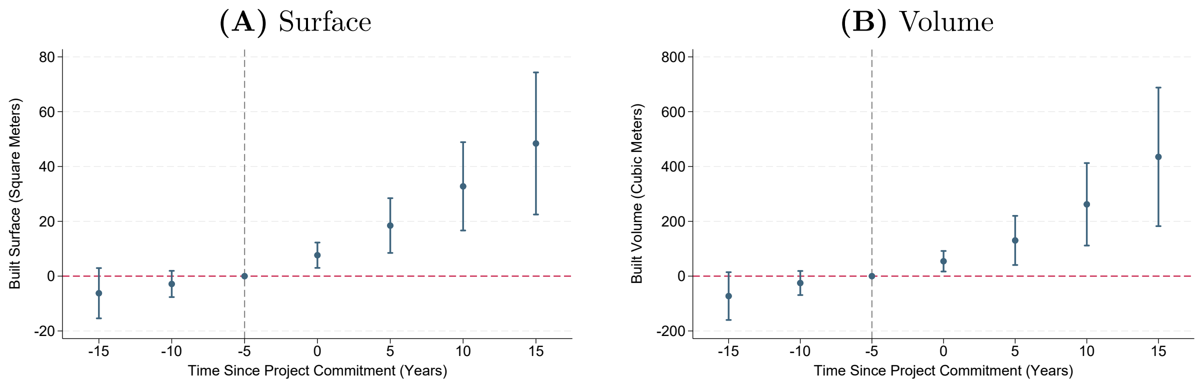


**Figure 3. Event Study Specification.** This figure plots the estimated coefficients and 95% confidence intervals for the event study specification using our preferred ring design strategy ($\underline{\theta} = 1.2$, $\bar{\theta} = 1.8$). The coefficients represent the difference in built surface (Panel A) or volume (Panel B) within and beyond the treatment threshold surrounding the project location from 15 years before to 15 years after the establishment year of each project. Appendix B shows the event study estimates using alternative thresholds to define treated and control units.

## 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 dimensions, 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 specification similar to 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 23 square meters per grid and volume by 190 cubic meters per grid, while non-residential development shows smaller effects (3 square meters per grid and 32 cubic meters per grid, respectively) with both being statistically significant. Our findings suggest that foreign aid projects tend to generate positive local amenities that attract disproportionately more residential development, consistent with previous studies showing 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 stimulate residential development in nearby areas. 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 the microregion level by taking the built-up sum (column 3) or the median grid (column 4), and then classify microregions as low if their measures were below the median across all 1,643 microregions. We find that areas with initially low built-up development experience much larger treatment effects. The interaction terms indicate that low-development areas show differential increases of 81-86 additional square meters per grid of surface and 561-630 additional cubic meters per grid of volume compared to more developed areas. These results align with fundamental differences in development constraints and costs in less developed areas. In less urbanized areas with abundant developable land, aid projects can catalyze new construction at relatively low cost, with more space for both surface and volume expansion. This finding has significant implications for foreign aid targeting, suggesting that projects located in underdeveloped areas can have a greater impact on local urbanization patterns.

In Column (5), we test for heterogeneity in the effects by the amount of project investment in dollars, grouping projects into "high amount" if their values exceed the median project amount in our sample. We find that the coefficients for the interaction term with "high amount" are not statistically significant for either surface or volume. To further investigate the influence of project amount on urbanization, we test alternative classifications for "high amount" projects. In the Appendix, Table C.2 presents the estimates of similar specifications to Column (5) in Table 2, but comparing projects in the top tercile versus bottom tercile (Column 2), and top quartile versus bottom quartile of the dollar amount distribution (Column 3). In most specifications, we find a positive coefficient for the high amount interaction term, suggesting that larger projects may indeed generate greater local urbanization effects. However, statistical significance is inconsistent across specifications, with only one showing statistically significant coefficients. Therefore, while point estimates are positive, the evidence is not strong enough to robustly establish that the dollar amount of a project has a differential impact on local urban development.[14]

## 5 Additional Results

To better understand 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 project types. The results are discussed and presented in more detail in Appendix C.

[14]It is important to mention that nearly half of the projects in our sample (825 of 1,643) lack information on amounts, which may contribute to the imprecision and inconsistency of these estimates.

**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 × Post | 22.894*** | 3.079*** | –11.279 | –13.658* | 24.040** |
| | (6.126) | (0.678) | (7.237) | (7.210) | (11.169) |
| × Low Built Surface (Sum) | | | 80.792*** | | |
| | | | (12.385) | | |
| × Low Built Surface (Median) | | | | 86.447*** | |
| | | | | (12.370) | |
| × High Amount | | | | | 7.379 |
| | | | | | (16.267) |
| Observations | 7,721,047 | 7,721,047 | 7,721,047 | 7,721,047 | 3,850,264 |
| Units | 1,103,549 | 1,103,549 | 1,103,549 | 1,103,549 | 550,307 |
| 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 × Post | 190.087*** | 32.374*** | –58.611 | –33.877 | 245.744** |
| | (58.351) | (6.793) | (76.880) | (80.567) | (99.305) |
| × Low Built Volume (Sum) | | | 630.454*** | | |
| | | | (117.196) | | |
| × Low Built Volume (Median) | | | | 560.703*** | |
| | | | | (116.408) | |
| × High Amount | | | | | –61.896 |
| | | | | | (145.305) |
| Observations | 7,721,047 | 7,721,047 | 7,721,047 | 7,721,047 | 3,850,264 |
| Units | 1,103,549 | 1,103,549 | 1,103,549 | 1,103,549 | 550,307 |
| Periods | 7 | 7 | 7 | 7 | 7 |
| Clusters | 1,643 | 1,643 | 1,643 | 1,643 | 818 |
| 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 amounts 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. Treatment and control units follow our preferred ring approach definition, excluding units between the inner and outer rings. Robust standard errors clustered at the level of projects are in parentheses. Statistical significance: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

First, we investigate whether the increases in built-up volume are simply reflecting the horizontal expansion of buildings. By definition, the expansion of built surface also leads to some expansion of the built volume. Therefore, because the effects on built volume mix both the extensive (more buildings) and intensive (taller buildings) margins, 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 use 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 shapes 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 demonstrate that foreign aid projects generate substantial and persistent increases in local urbanization, with treatment effects of approximately 50 square meters of additional built-up surface and more than 400 cubic meters of additional built-up 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 development 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 strong evidence that the dollar amount of aid projects generates heterogeneous responses to local 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 strategically placing aid projects, particularly in less-urbanized areas, can effectively catalyze local urban development patterns. 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.

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# Internet Appendix to
# "Foreign Aid Shapes Local Urban Development"

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# 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.

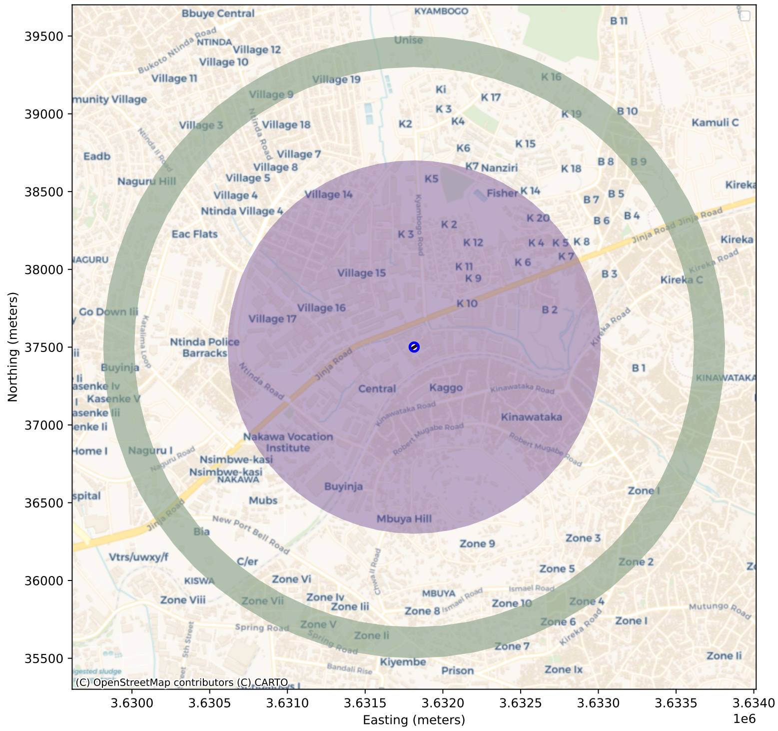


**Figure A.1. Illustration of the Identification Strategy**. This figure illustrates the identification strategy discussed in Section 3.2. At the center, it plots the Uganda Industrial Research Institute, funded by Chinese grants in Nakawa, Uganda, a project classified as "industry, mining and construction." As we describe in Eq. (3), we define a spatial threshold (in this example, $\underline{\theta} = 1.2$, $\bar{\theta} = 1.8$) and consider all grids located within a distance $\underline{\theta}$ =1.2km (purple ring) from the project as treated, while those located at a distance greater than $\bar{\theta}$ =1.8km but smaller than 2km (green ring) are defined as our control units.

**(A)** Original Categories **(B)** Grouped Categories

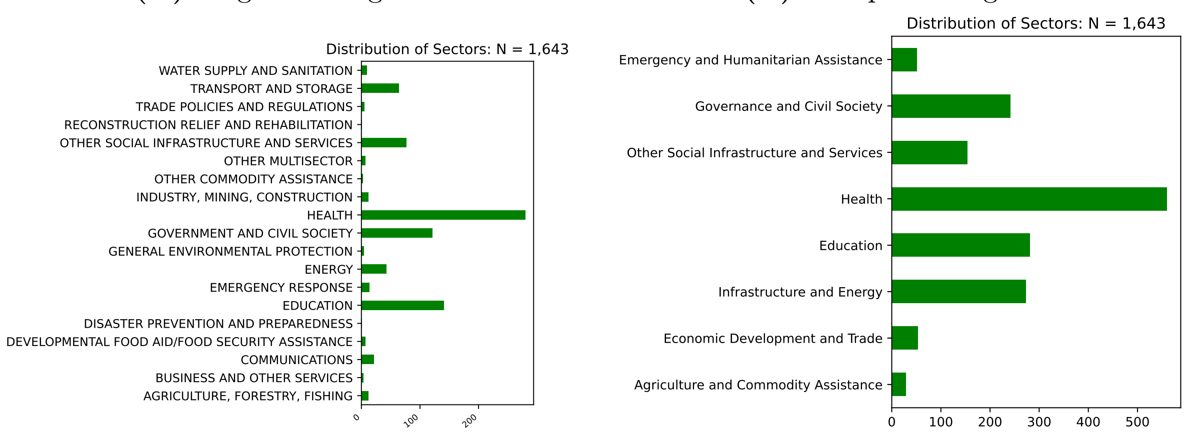


**Figure A.2. Type Distribution of Aid Projects**. This figure shows the counts of different types of projects in Africa between 2000 and 2021. Panel A is the definition of projects in the original Aid Dataset (Goodman et al., 2024), and in Panel B, we group related types of projects into eight different 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 our preferred ring design strategy ($\underline{\theta} = 1.2$, $\bar{\theta} = 1.8$). 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 ring designs to define treatment exposure. 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.

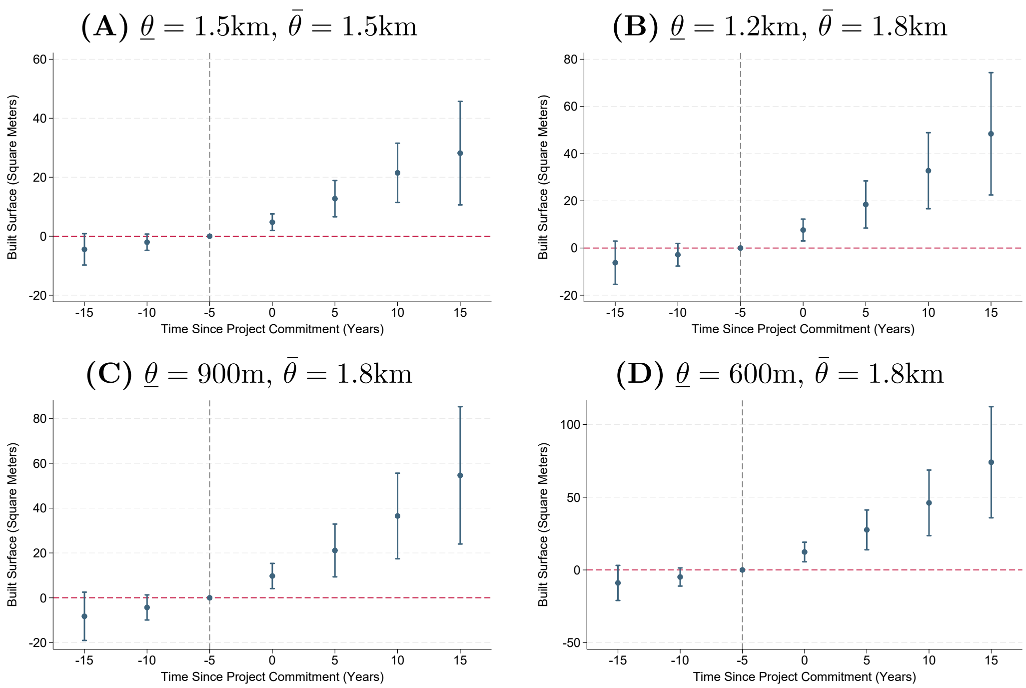


**Figure B.1. Event Study under alternative ring designs: Built Surface.** This figure plots the estimated coefficients and 95% confidence intervals for the event study specification using (A) $\underline{\theta} = 1.5$km, $\bar{\theta} = 1.5$km, (B) $\underline{\theta} = 1.2$km, $\bar{\theta} = 1.8$km, (C) $\underline{\theta} = 900$m, $\bar{\theta} = 1.8$km, and (D) $\underline{\theta} = 600$m, $\bar{\theta} = 1.8$km corresponding to the specification in equation (4).

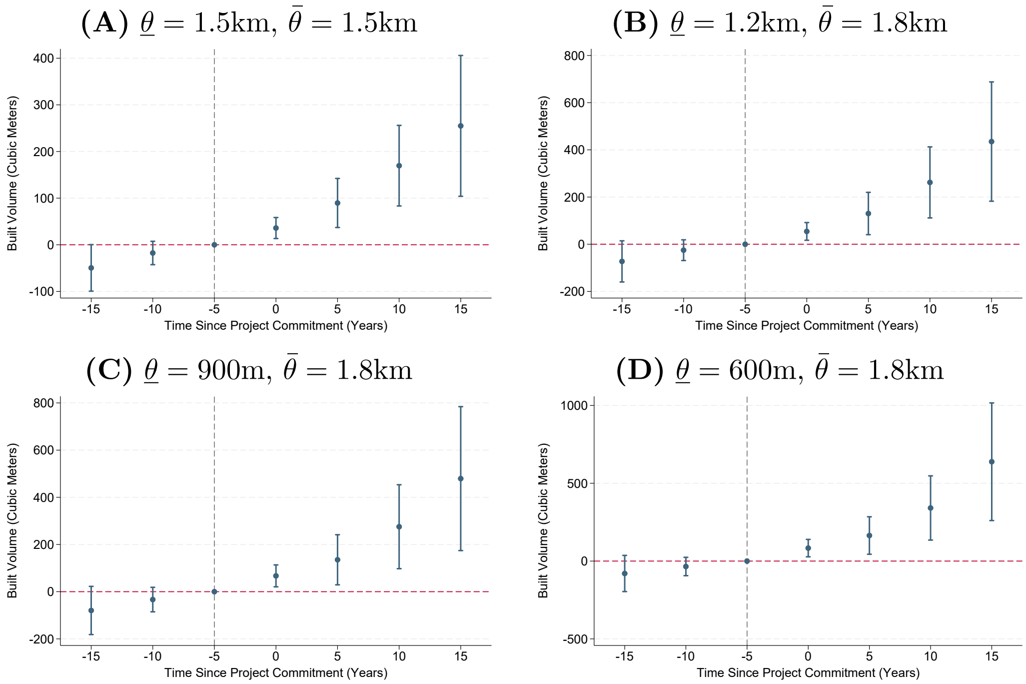


**Figure B.2. Event Study under alternative ring designs: Built Volume.** This figure plots the estimated coefficients and 95% confidence intervals for the event study specification using (A) $\underline{\theta} = 1.5$km, $\bar{\theta} = 1.5$km, (B) $\underline{\theta} = 1.2$km, $\bar{\theta} = 1.8$km, (C) $\underline{\theta} = 900$m, $\bar{\theta} = 1.8$km, and (D) $\underline{\theta} = 600$m, $\bar{\theta} = 1.8$km 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.

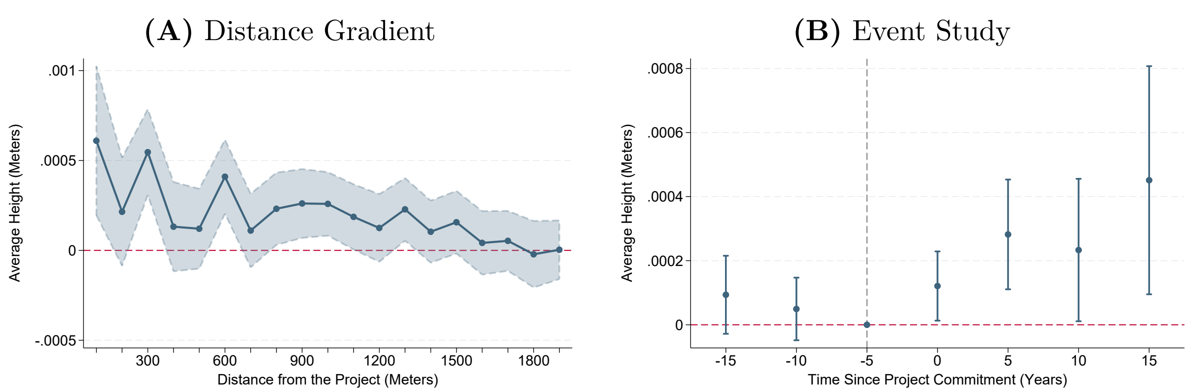


**Figure C.1. Effects on Height.** Panel A plots the estimated coefficients of distance dummies for every 100 meters away from the center of the project location and 95% confidence intervals according to the specification in equation (1). Panel B plots the estimated coefficients and 95% confidence intervals for the event study specification using the ring strategy ($\underline{\theta} = 1.2$, $\bar{\theta} = 1.8$) as described 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.

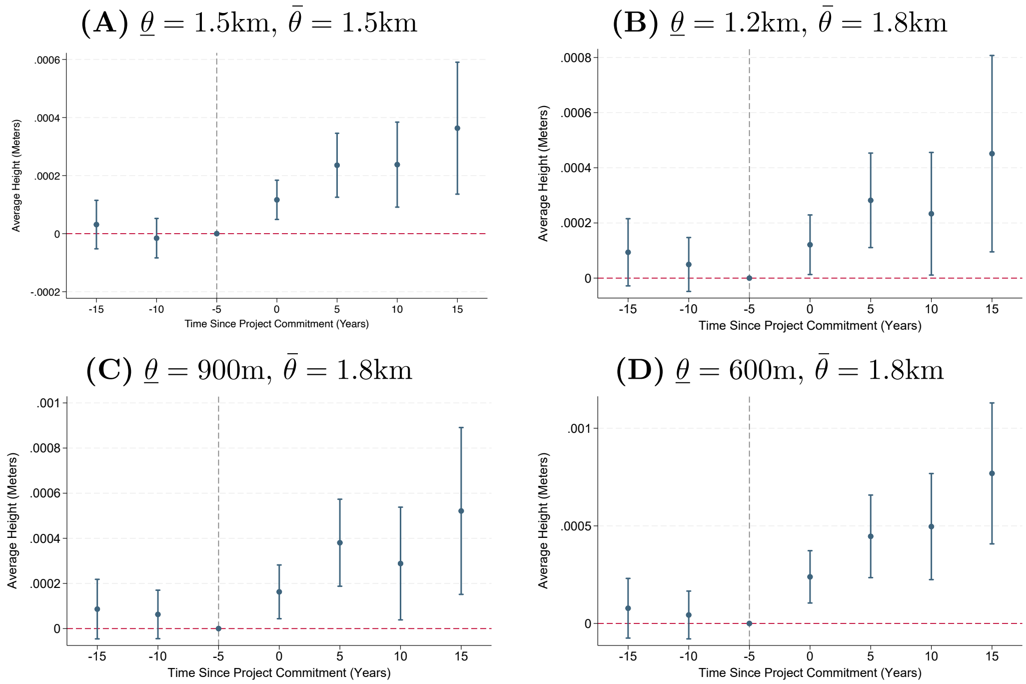


**Figure C.2. Event Study Specification under alternative threshold designs: Height.** This figure plots the estimated coefficients and 95% confidence intervals for the event study specification using (A) $\underline{\theta} = 1.5\text{km}$, $\bar{\theta} = 1.5\text{km}$, (B) $\underline{\theta} = 1.2\text{km}$, $\bar{\theta} = 1.8\text{km}$, (C) $\underline{\theta} = 900\text{m}$, $\bar{\theta} = 1.8\text{km}$, and (D) $\underline{\theta} = 600\text{m}$, $\bar{\theta} = 1.8\text{km}$ corresponding to the specification in equation (4). The coefficient represent the difference between height within the inner ring and beyond the outer ring centered at 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 | Economic Development and Trade | Infrastructure and Energy | Education | Health | Social Infrastructure and Services | Government and Civil Society | Emergency and Humanitarian Assistance |
|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| Distance × Post | –0.023 | –0.079*** | –0.022** | –0.034** | –0.028*** | –0.032* | 0.006 | 0.037** |
| | (0.017) | (0.023) | (0.009) | (0.015) | (0.008) | (0.018) | (0.010) | (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 A. Built Volume**

| | Agriculture and Commodity Assistance | Economic Development and Trade | Infrastructure and Energy | Education | Health | Social Infrastructure and Services | Government and Civil Society | Emergency and Humanitarian Assistance |
|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| Distance × Post | 0.016 | –0.721*** | –0.135 | –0.170 | –0.226*** | –0.210 | 0.072 | 0.086 |
| | (0.172) | (0.207) | (0.083) | (0.147) | (0.064) | (0.154) | (0.109) | (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* × *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.

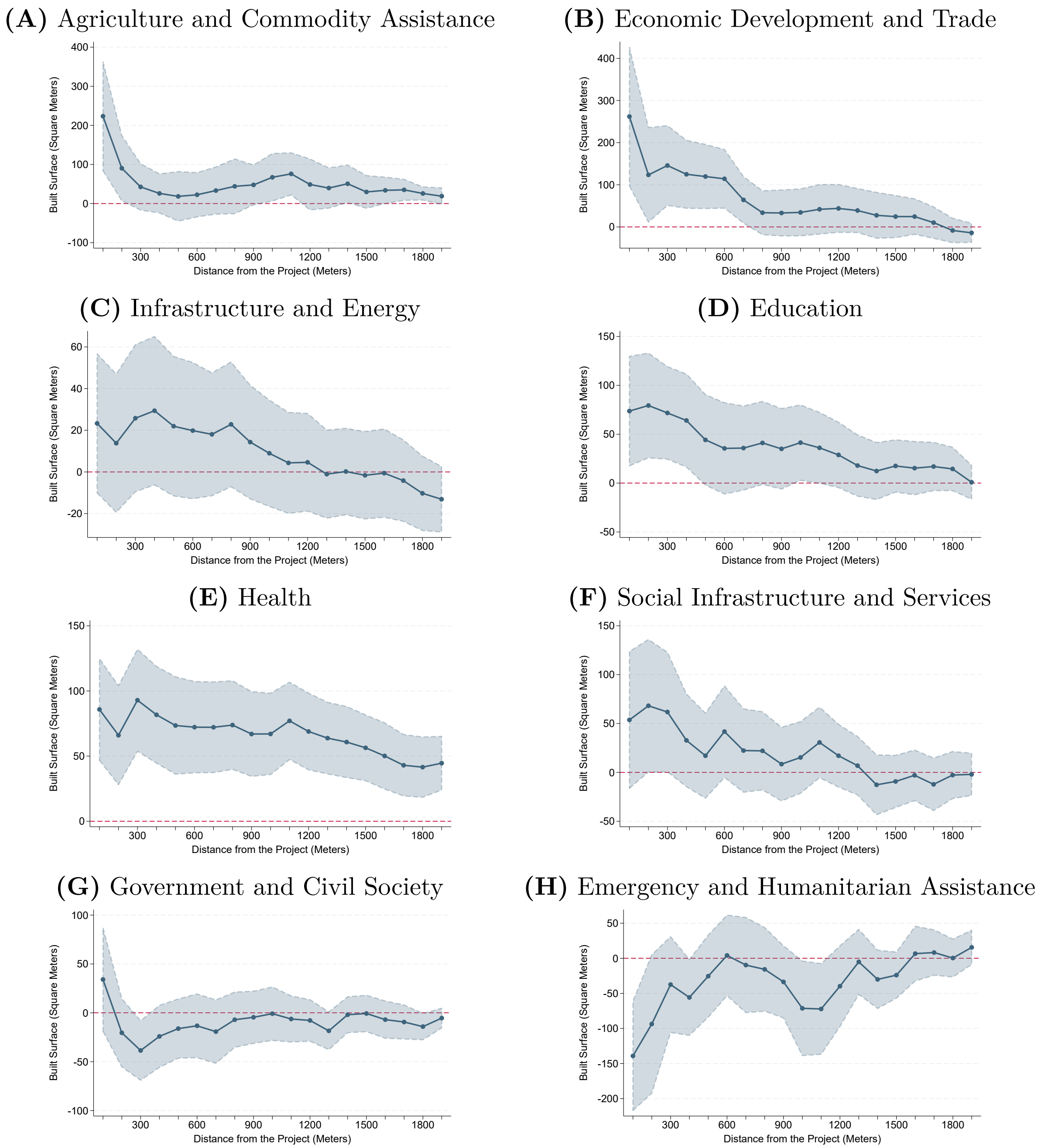


**Figure C.3. Distance Gradient by Project Type: Built Surface.** This figure plots the estimated coefficients of distance dummies for every 100 meters away from the center of the project location and 95% confidence intervals according to the specification in equation (1). We estimate the specification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

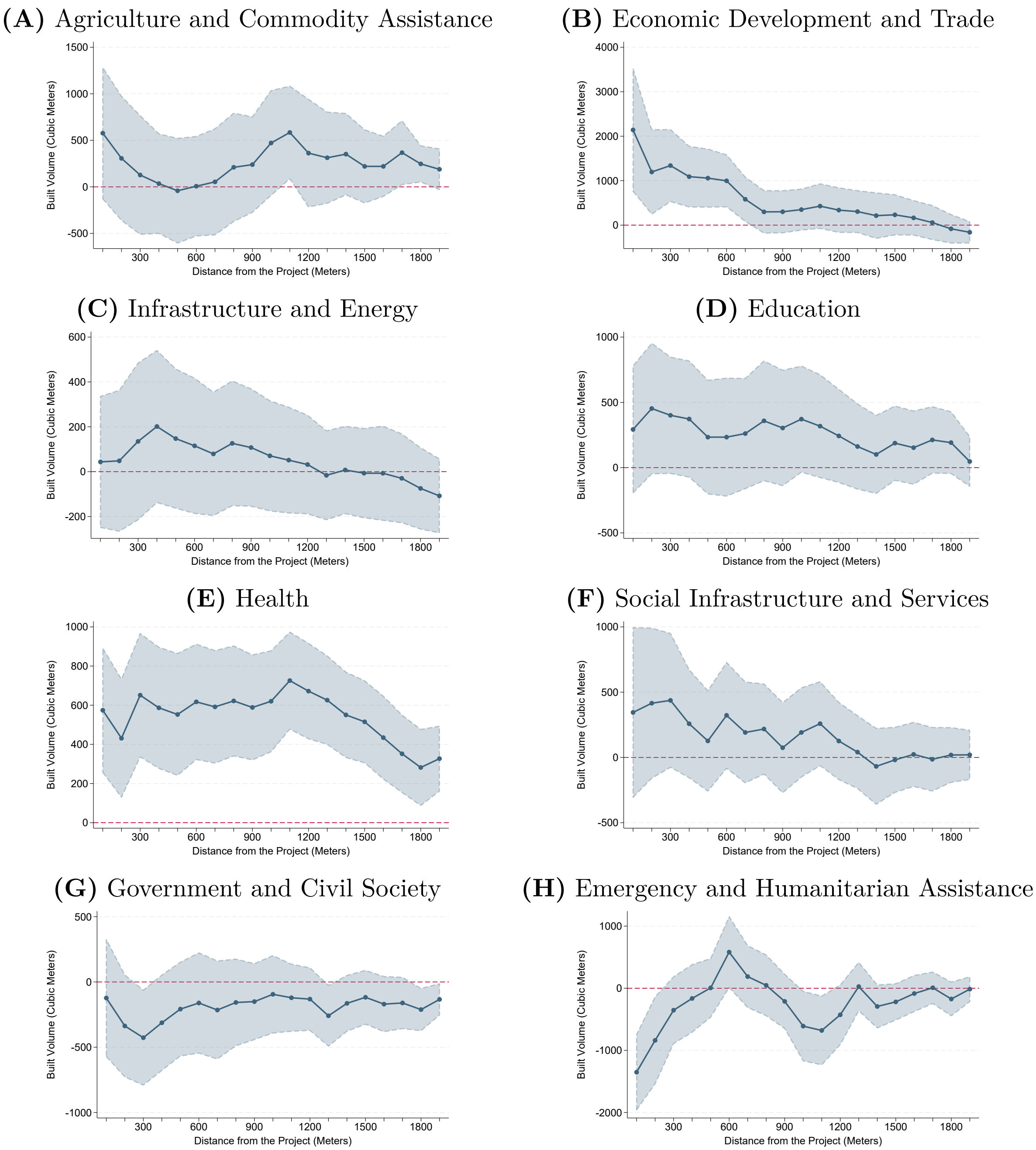


**Figure C.4. Distance Gradient by Project Type: Built Volume.** This figure plots the estimated coefficients of distance dummies for every 100 meters away from the center of the project location and 95% confidence intervals according to the specification in equation (1). We estimate the specification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

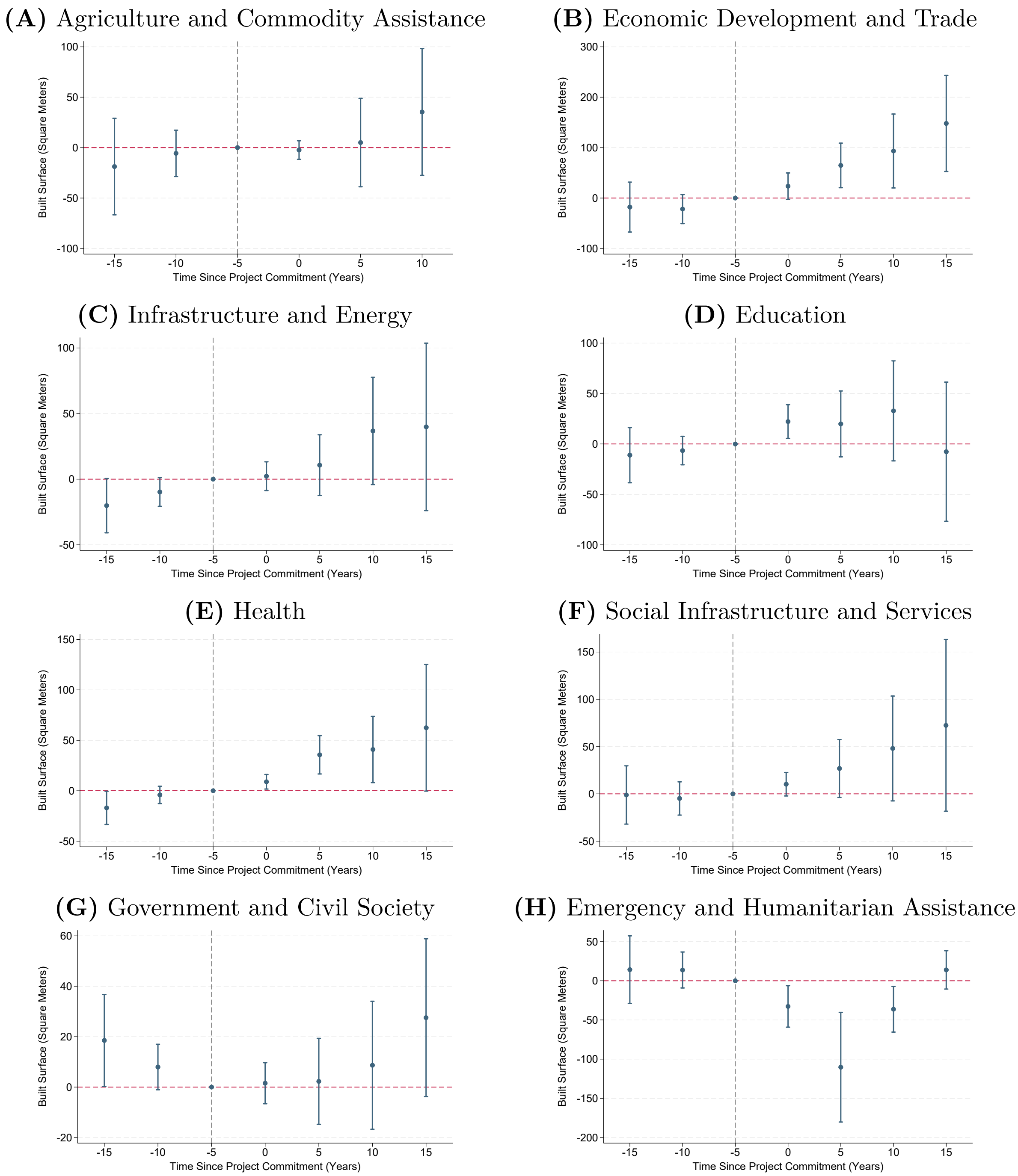


**Figure C.5. Event Study by Project Type: Built Surface.** This figure plots the estimated coefficients and 95% confidence intervals for the event study specification using $\underline{\theta} = 1.2$km, $\bar{\theta} = 1.8$km as the treatment and control cut-offs corresponding to the specification in 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.

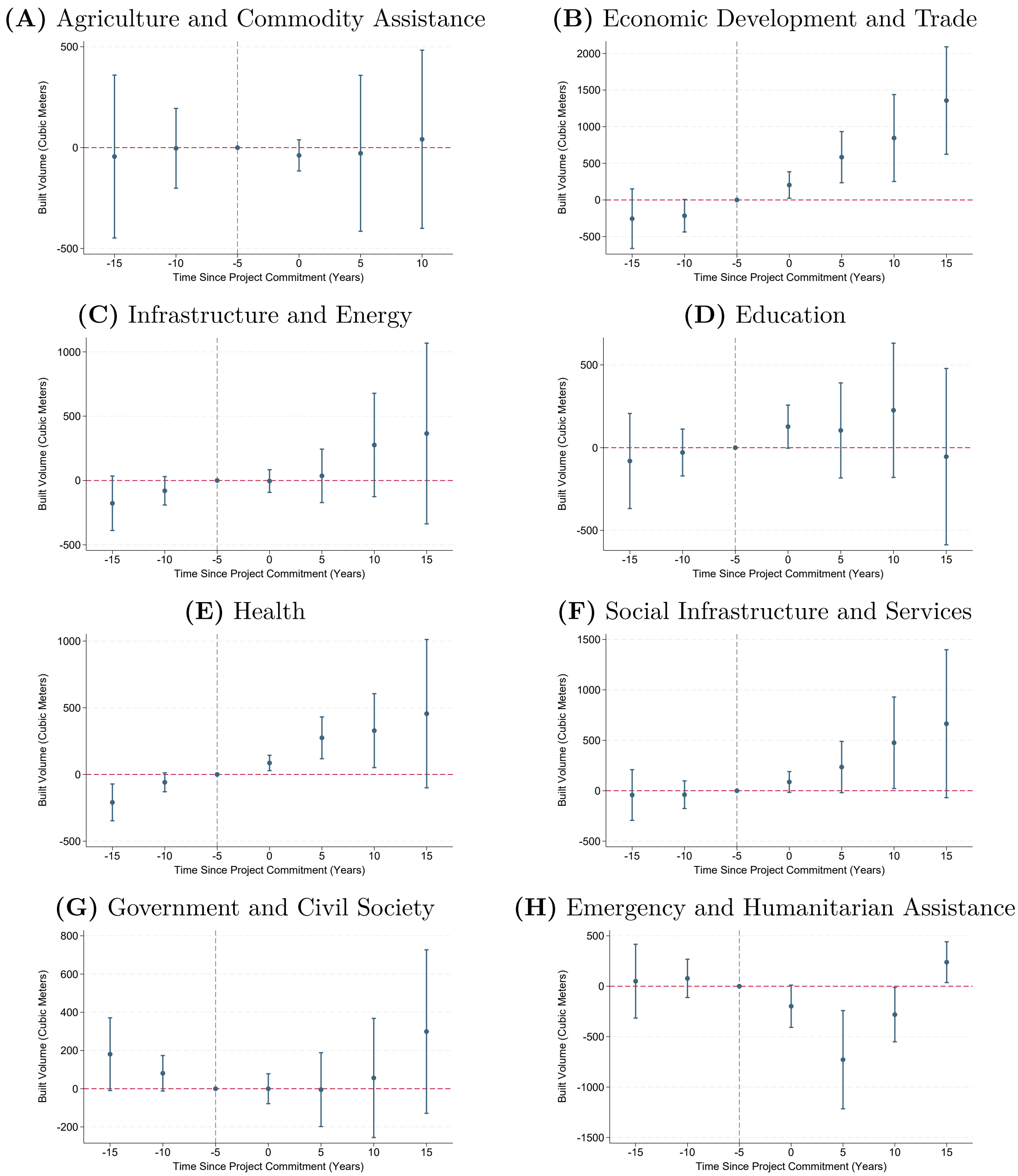


**Figure C.6. Event Study by Project Type: Built Volume.** This figure plots the estimated coefficients and 95% confidence intervals for the event study specification using $\underline{\theta} = 1.2$km, $\bar{\theta} = 1.8$km as the treatment and control cut-offs corresponding to the specification in equation (4) for each type of project separately.

## C.3 Distance gradient under extended areas

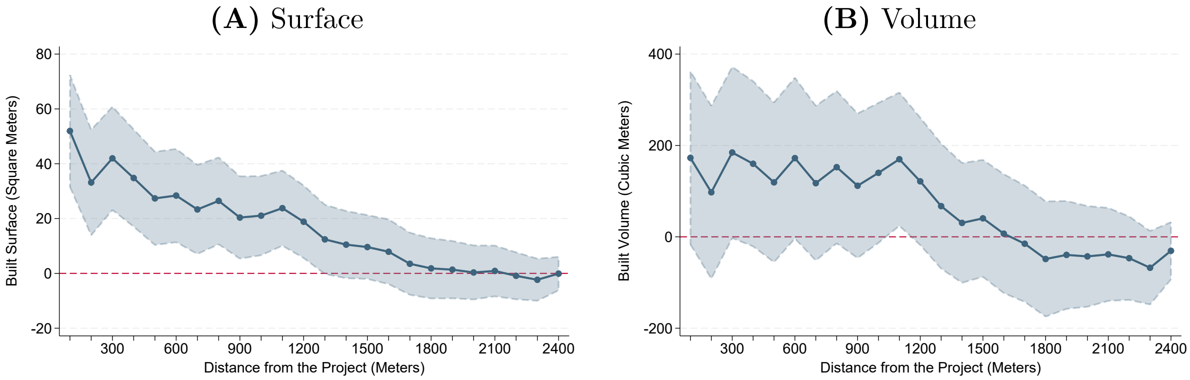


**Figure C.7. Distance gradient in 2.5 km radius area.** This figure plots the estimated coefficients of distance dummies for every 100 meters away from the center of the project location and 95% confidence intervals according to the specification in equation (1). It is similar to Figure 2, while we extend the area of the analysis to a 2.5 km radius with grids with distances between 2.4 and 2.5 km serving as the reference group. 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.

## C.4 Alternative measures for high amount projects

**Table C.2. Heterogeneity to Dollar Amount: Alternative measures**

**Panel A. Built Surface**

| | *Measures for High Amount* | | |
|---|---|---|---|
| | Above Median | Top Tercile | Top Quartile |
| | (1) | (2) | (3) |
| Treated × Post | 24.040** | -12.824 | -10.921 |
| | (11.169) | (11.792) | (13.083) |
| × High Amount | 7.379 | 39.080** | 35.649 |
| | (16.267) | (17.562) | (22.253) |
| Observations | 3,850,264 | 2,558,651 | 1,919,620 |
| Units | 550,307 | 365,681 | 274,385 |
| Periods | 7 | 7 | 7 |
| Clusters | 818 | 544 | 408 |
| R-squared | 0.98 | 0.98 | 0.98 |

**Panel B. Built Volume**

| | *Measures for High Amount* | | |
|---|---|---|---|
| | Above Median | Top Tercile | Top Quartile |
| | (1) | (2) | (3) |
| Treated × Post | 245.744** | -43.953 | -13.466 |
| | (99.305) | (99.198) | (110.881) |
| × High Amount | -61.896 | 246.897 | 190.434 |
| | (145.305) | (153.591) | (197.094) |
| Observations | 3,850,264 | 2,558,651 | 1,919,620 |
| Units | 550,307 | 365,681 | 274,385 |
| Periods | 7 | 7 | 7 |
| Clusters | 818 | 544 | 408 |
| R-squared | 0.98 | 0.99 | 0.99 |

*Notes:* This table reports the heterogeneous effects of foreign aid projects on grid-level urbanization by the dollar amount of projects. Column (1) repeats the estimates in Table 2, and classifies projects with amounts above the median as high amount projects. Column (2) presents the estimates, classifying as high amount those projects with amounts higher than the top tercile, relative to those in the bottom tercile of the distribution. Column (3) presents the estimates when we classify projects as high-amount if their amounts exceed the top quartile, relative to those in the bottom quartile of the amount distribution. Treatment and control units follow our preferred ring approach definition, excluding units between the inner and outer rings. Robust standard errors clustered at the level of projects are in parentheses. Statistical significance: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.