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When Does Success Spread? Evidence from Project-Level Evaluations in Africa

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When Does Success Spread? Evidence from Project-Level Evaluations in Africa *

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Abstract

This paper examines whether the success of prior aid projects affects the performance of subsequent ones based on a study of World Bank projects in Africa. While existing research has shown that aid effectiveness depends on macroeconomic conditions, institutional quality, and managerial capacity, far less is known about whether project success generates localized improvements that extend beyond its immediate boundaries. Using geocoded data and independent evaluation ratings of World Bank projects, this study finds that local success does not systematically translate into higher performance for subsequent projects. In fact, it can sometimes make it less likely for future projects to achieve top outcomes. I also found evidence of a negative effect in localities with dense exposure to highly satisfactory projects. Regions with a mix of highly rated and moderately rated projects tend to do better in the future than those with only top-rated projects. This means that while lessons have been learned from very successful projects, having too many of these in one place can have negative spillovers. Therefore, close monitoring is needed in regions with high concentrations of top-performing projects to ensure that early successes and lessons learned are managed appropriately, preventing them from undermining later performance.

Keywords: Aid effectiveness, World Bank, project success, localized learning

JEL Classification Numbers: F35, H43, O22, O55

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1 Introduction

Why some development projects succeed while others fail remains an important question in research on the effectiveness of foreign aid. For several decades, research on this subject was dominated by macroeconomic analyses and aggregate aid data, and it became clear that the quality of institutions, governance, and policy environments is crucial in determining whether aid promotes or inhibits economic growth (Dalgaard et al., 2004; Demir & Duan, 2023; Dollar & Burnside, 1999; Temple, 2010). However, this area remains under-researched to date, and the available evidence suggests that project-level factors matter, with performance varying widely across projects even in similar institutional contexts (Bulman et al., 2016; Denizer et al., 2013). Consequently, aid effectiveness depends not only on macro-level factors but also on the quality of project design and implementation.

Despite such progress, a key aspect of aid effectiveness remains unexploited: whether success in one project may affect the outcomes of others in its geographical proximity. It seems likely that “success” or “failure” in one project might spread to others in its geographical surroundings and this carries significant implications for aid effectiveness. Since successful projects create local learning, enhance institutional coordination, and strengthen implementation capacity, one might expect subsequent projects in the same area to perform better. Conversely, continued concentration of resources and managerial capacity in already successful areas might generate diminishing returns (Collier, 2006; Dalgaard, 2008; Temple, 2010) or learning fatigue, representing stagnation in performance. Such contrasting hypotheses emphasize an essential research question that, to date, remains unanswered: whether prior successful projects improve or hinder the outcomes of subsequent aid interventions.

To address this question, I investigate whether project success spreads locally by examining World Bank-funded projects in Africa. Detailed geocoded data and evaluation ratings from the Independent Evaluation Group (IEG) are used to assess whether the success of earlier nearby projects affects the performance of subsequent projects in the same locations. By linking future project outcomes to past aid activities in proximate areas, the analysis measures the impact of local learning in development interventions. Overlapping project timelines are used to estimate whether earlier local success predicts improved performance in later projects.

This analysis adds to several areas of existing research. First, it builds on studies of aid effectiveness at both the macro and project levels that highlight the role of institutional quality and management in shaping development results (Ashton et al., 2022; Kilby, 2015; Shin et al., 2017; Temple, 2010; Winters, 2019; Wood et al., 2020). While these studies show that governance and project management are both important, they do not explore whether learning and performance improvements spread across locations. Second, this research adds to recent work on how aid is targeted and allocated (BenYishay et al., 2022;

Briggs, 2018; Demir & Duan, 2023; Öhler & Nunnenkamp, 2014; Öhler et al., 2019; Winters, 2010), which has found significant differences in how aid is distributed within countries. Yet these authors provide limited insights into the underlying mechanisms driving spatial heterogeneity in project performance.

Empirically, the present paper uses two World Bank datasets that combine project-level evaluation ratings (IEG, 2025) with geospatial data on project locations across 46 African countries (AidData, 2017). Each project is assigned an outcome rating from the IEG’s evaluation framework, which assesses relevance, efficiency, and effectiveness at completion. These ratings are merged with the AidData geocoded project database to create spatial linkages among projects located within defined distance buffers. This empirical strategy makes it possible to estimate localized exposure effects, capturing whether proximity to previously successful projects predict higher performance for subsequent ones. The analysis further controls for country, sector, and time fixed effects, ensuring that estimated relationships reflect local spillovers rather than confounding factors.

The findings reveal that proximity to successful projects does not systematically increase the probability of subsequent project success. In some cases, repeated exposure to highly rated nearby projects is associated with slightly lower performance, suggesting learning saturation. Further analysis shows that the composition of prior project experiences matters: areas that previously hosted both highly and moderately rated projects tend to sustain stronger future performance, while areas repeatedly exposed only to top-rated projects exhibit diminishing returns. This finding contributes to the learning-by-doing literature since it shows that while exposure to successful projects facilitates adaptation, high concentrations of such exposure are associated with diminishing marginal returns (Argote et al., 1990; Benkard, 2000).

The results have important implications for both research and practice. They suggest that aid effectiveness is not only determined by governance and management quality but also by local project portfolios. Concentrating interventions in historically successful areas may reinforce existing capacities but can also lead to rigidity, with implementing agencies relying excessively on established methods. Conversely, moderate variation in project experience may stimulate innovation and improve adaptability. These insights showcase the need for development agencies to consider spatial and learning dynamics in aid allocation and project design decisions.

The remainder of the paper is organized as follows. Section 2 reviews earlier studies using World Bank project data and places this research in that context. Section 3 explains the data sources and construction of variables. Section 4 describes how the study tests whether local exposure to past project success affects later outcomes. Section 5 presents the main findings, and Section 7 checks how consistent the results are through a number of robustness checks. Section 8 discusses the implications of the results for the broader aid effectiveness literature and finally, Section 9 concludes.

2 Related Literature

The literature on aid effectiveness has evolved from early macroeconomic assessments of aggregate aid flows toward more granular analyses of project-level performance. A key question uniting both perspectives is whether a project's successful implementation depends primarily on country-level institutional quality or on project-specific management and design.

A large body of research has examined the conditions under which aid produces positive outcomes (Ashton et al., 2022; Blum, 2014; Briggs, 2019; Bulman et al., 2016; Burnside & Dollar, 2004; Denizer et al., 2013; Isham et al., 1997; Prokopy, 2005; Temple, 2010; Winters, 2010), beginning with macro-level analyses that emphasize the role of institutional quality and governance as key determinants of project success. In terms of institutional quality, Temple (2010) highlighted that foreign aid is neither inherently effective nor ineffective, but rather conditional on the quality of recipient institutions and governance systems. The author emphasized that strong administrative capacity and sound macroeconomic management create the conditions for aid to achieve tangible development outcomes. Similarly, Ashton et al. (2022) found that institutional quality, as captured by country policy and institutional assessment scores, remains one of the most consistent predictors of project success. Both studies converge on the principle that robust institutions provide an enabling environment for aid implementation.

However, while these macro-level conditions remain crucial, they are insufficient to explain the substantial variation observed within countries. Even in environments with similar governance ratings, project outcomes often vary widely. This limitation has motivated a growing body of research that shifts the focus from macroeconomic and institutional determinants to project-level dynamics, including management quality, supervision intensity, and local implementation capacity (Chauvet et al., 2010a; Heinzel & Liese, 2021; Honig, 2020; Honig et al., 2022; Ika et al., 2012; Kilby, 2000, 2015; Limodio, 2021; Metzger, 2013). These studies consistently find that project design and preparation processes play a key role in determining outcomes, with effective supervision, strong leadership, and adaptive management often compensating for weaker institutional contexts.

Together, these studies suggest that the success of aid projects depends on both internal managerial processes and external institutional environments, rather than aid volume or donor presence alone. Yet, despite this progress, relatively little is known at present about whether successful projects generate localized performance improvements beyond their immediate boundaries, or whether success remains confined to specific areas.

The present paper contributes to this literature in three ways. First, it provides, to the best of the author's knowledge, the first systematic evidence on localized performance spillovers in aid projects, identifying whether prior success in nearby areas enhances or diminishes subsequent outcomes. Unlike

Denizer et al. (2013) and Bulman et al. (2015), who focus on cross-country patterns, this paper leverages spatially linked project-level data to analyze within-country performance diffusion. Second, it extends the literature on project management and organizational learning (Ashton et al., 2022; Kilby, 2015; Metzger, 2013)) by distinguishing between learning that occurs within the same donor institution and that which propagates geographically across projects. Finally, the present paper contributes to the relatively small but growing literature on aid targeting in aid implementation (BenYishay et al., 2022; Briggs, 2018; Demir & Duan, 2023), which is conceptually closest to this paper. Briggs (2018) and BenYishay et al. (2022) use geocoded aid data to show that allocation is spatially clustered. Their results might suggest that exposure to nearby aid activity shapes local administrative capacity and project outcomes, although the authors stop short of estimating direct links between prior and subsequent outcomes. The present study contributes to this emerging literature by providing the first large-scale test of localized performance spillovers in development projects across Africa.

3 Data

3.1 Variables

This section describes the datasets used in the analysis and presents descriptives that motivate the empirical approach. The study relies on two primary data sources (i) geocoded project-level information from the AidData database (AidData, 2017) and (ii) project evaluation outcomes from the World Bank’s IEG overall ratings (IEG, 2025). Examining the dynamics of historical project outcomes within specific geographical areas provides valuable insights into how experience of local implementation shapes future project performance.

Dependent Variable: The geocoded AidData dataset tracks World Bank-financed projects implemented across Africa between 1995 and 2014. This location-level dataset links each project to its recipient country and includes detailed information on approval year, start and end dates, financial commitments and disbursements (in USD), task team leader (TTL) names, and overall outcome score. AidData’s evaluation ratings are not fully up to date; I complement these data with project evaluations retrieved directly from the IEG website (IEG, 2025), which provides updated ratings for projects completed between 1980 and 2025. The merged dataset substantially increases the coverage of evaluated projects, recovering evaluations for approximately 17% of projects that were previously missing from AidData. It also reflects the most recent assessments for projects that have been re-evaluated¹. I retain the IEG ratings, as these

¹Approximately 35 projects exhibit discrepancies between the two sources.

are more frequently updated and thus considered to be more reliable.

While project evaluation data inevitably have limitations, they nonetheless embody the accumulated experience and professional judgment of World Bank and IEG staff regarding project performance (Denizer et al., 2013). Consequently, they remain a valuable empirical basis for analyzing patterns of localized learning effects. Consistent with this perspective, I integrate evaluations from both AidData and the IEG to construct a more comprehensive dataset. The IEG evaluates all completed projects independently within the World Bank, assigning each an overall outcome score on a 6-point scale: 1 (Highly Unsatisfactory), 2 (Unsatisfactory), 3 (Moderately Unsatisfactory), 4 (Moderately Satisfactory), 5 (Satisfactory), and 6 (Highly Satisfactory) (see Bedasso (2024), Chauvet et al. (2010b), and Ika et al. (2012) for discussions on the World Bank’s evaluation framework). To streamline interpretation and address the limited frequency of extreme ratings, I collapse the 6-point scale into three performance categories: Less Satisfactory (LS, scores 1–2), Moderately Satisfactory (MS, scores 3–4), and Highly Satisfactory (HS, scores 5–6). This transformation follows earlier studies noting that most projects are rated between 2 and 5, with few cases at the extremes (Asare, 2025).

The main dependent variable is a binary indicator equal to 1 if a project achieves an HS rating. Focusing on HS outcomes offers three advantages. First, it highlights the determinants of exceptional project success rather than marginal improvements in performance (Denizer et al., 2013). Second, given the ordinal nature of the IEG rating scale, the binary specification avoids imposing cardinal assumptions and gives clear-cut interpretations in terms of the likelihood of achieving high performance. Third, the distribution of ratings is heavily centered around “MS,” while lower categories are rare. Aggregating all non-HS outcomes into a single reference group improves statistical precision, mitigates instability in ordered response models and facilitates identification within the empirical framework.

Main Explanatory Variable – Prior Success: Using the same AidData dataset, I measure prior local exposure to aid over time. Each project record includes start and end dates as well as the year of evaluation. Using this information, I identify all projects completed before the start of a given focal project and located within a defined spatial proximity. This procedure allows me to construct a temporal and spatial measure of prior aid exposure. Projects are categorized into three outcome groups based on their overall evaluation scores: HS, MS, and LS. For each project location, I record whether it has previously received aid in any of these categories and also count the number of such occurrences within the specified buffer. All baseline estimates are based on a 25-kilometer (km) buffer, except for the robustness checks with alternative buffer sizes reported in Subsection 7.2 (see Section 3.2 for details on buffer construction). Figure 1b illustrates this spatial matching approach in which prior aid projects completed before the focal project’s start date are identified and aggregated within the buffer area.

Covariates: To isolate the local learning and spillover effects of prior projects, the analysis controls for a range of spatial and environmental factors that could simultaneously affect both aid location and overall performance. Following recent literature on subnational aid effectiveness (BenYishay et al., 2022; Briggs, 2018; Dannemann & Gören, 2025), I use average population density from the Center for International Earth Science Information Network (CIESIN, 2018). This is included because donor agencies often allocate more projects to densely populated areas which are also likely to have stronger institutions and better service delivery capacity. If unaccounted for, these demographic factors could bias the estimated effects of prior exposure upward, simply because populous areas host more projects and perform better in general. Controlling for local population within each proximity helps ensure that estimated relationships reflect variation in project performance conditional on population, rather than just the tendency for donors to invest in densely populated areas.

Additionally, local conflict data is obtained from the UCDP Georeferenced Event Dataset (GED) (Davies et al., 2025; Sundberg & Melander, 2013). Conflicts can heavily influence both the allocation of aid and its outcomes. Donors may avoid conflict-prone regions, while ongoing violence can directly disrupt project implementation, increase costs, or reduce effectiveness. To control for these factors, I include a measure of local conflict incidence (i.e., no conflict events during the project). This ensures that the estimated effects of prior project exposure are not confounded by differential exposure to instability. Similar subnational studies find that conflict intensity significantly moderates aid effectiveness (Crost et al., 2014; Moscona, 2025; Nunn & Qian, 2014).

Subsequently, nighttime light intensity from NASA’s Earth Observation Group (Doll et al., 2000; Elvidge et al., 2017; Ghosh et al., 2009; Hsu et al., 2015; Image and data processing by Earth Observation Group, 2025) spanning the 1992–2014 period, with recent data between 2015 and 2021 from Bitzer and Gören (2024), serves as a proxy for economic development and urbanization (Henderson et al., 2012). Including this measure takes into account that the richer or more urbanized regions are more likely to receive projects and to implement them successfully. Furthermore, I account for accessibility (data from Nelson et al. (2019)), measured as the average travel time to the nearest city (i.e., a city with inhabitants of $\geq 50,000$), which captures the ease of monitoring and implementation (Dannemann & Gören, 2025; Öhler et al., 2019; Weiss et al., 2018). Projects in remote or isolated areas often face logistical difficulties, cost overruns, and delays. Accounting for this prevents these constraints from being misinterpreted as a lack of accessibility.

Finally, climatic conditions, average precipitation, temperature and the Standardized Precipitation-Evapotranspiration Index (SPEI) are included to control for environmental shocks that may affect both donor allocation and project outcomes. Extreme weather or droughts can impact agricultural productivity,

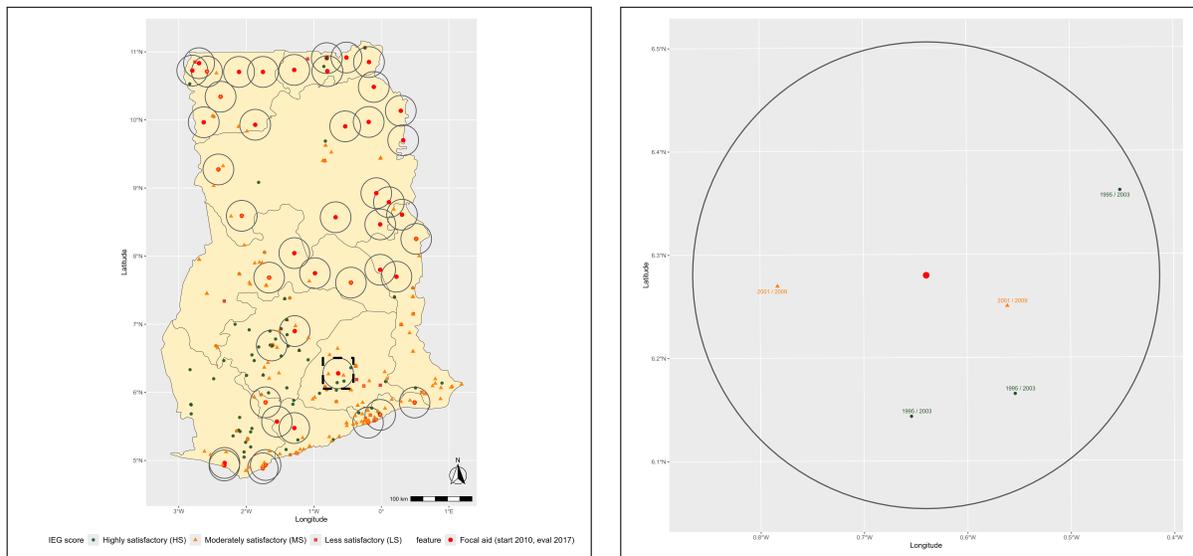
infrastructure durability, and economic performance (Burke et al., 2015; Dannemann & Gören, 2025; Dell et al., 2012). Together, the inclusion of ADM₂, evaluation-year, team-leader and sector fixed effects further absorbs unobserved regional characteristics, temporal shocks, and institutional heterogeneity.

3.2 Identification Strategy and Sample Processing

Spatial Buffer: The unit of analysis is the project location. To capture localized learning dynamics, I exploit the geographic allocation of World Bank aid across Africa by identifying prior project exposure within a 25km radius around each site.² The baseline buffer size of 25km follows recent aid evaluation studies that identify aid effectiveness within local administrative clusters of World Bank operations (Bitzer & Gören, 2024; Briggs, 2018; Dannemann & Gören, 2025). The 25km radius serves as a plausible spatial scale for organizational learning and implementation externalities. This choice reflects three potential channels through which proximity may be of importance: (i) knowledge diffusion, whereby information and practices could spread across nearby project sites; (ii) shared infrastructure and governance context, as geographically proximate projects may rely on similar transport networks, power supply, and administrative systems; and (iii) implementation overlap, since nearby projects could be overseen by the same task team leader (TTL), local office, or implementing partner. The 25km buffer is therefore small enough to capture shared local conditions but broad enough to encompass interacting project clusters. Results are robust to alternative buffer sizes of 5km to 50km, which yield qualitatively similar, though slightly attenuated, effects.

Using Ghana to demonstrate the spatial matching and counting procedure, Figure 1a (left-hand panel) maps World Bank project locations across the country. Each circle represents a 25km buffer drawn around projects starting in 2010, which serves as the focal aid intervention (shown as the large red point). The remaining points denote projects that were completed prior to the commencement of the focal project. The dashed square highlights the area that is enlarged in the right-hand panel. The zoomed-in view in Figure 1b (right-hand panel) identifies five projects that were evaluated before the focal project began. Of these, three received HS ratings and two were rated MS while a unique count records a single exposure for each rating category. All five projects predate the focal intervention. The buffer surrounding each

²Related studies use grid cells to define spatial units when examining aid effects on poverty or growth (Bitzer & Gören, 2024; Briggs, 2018) and on conflict (Moscona, 2025). A buffer-based exposure measure is preferred to grid cells because this defines spatial proximity directly in terms of geographical distance, which is independent of arbitrary partitioning of space. Grid cells impose fixed boundaries and encompass areas that are too large and heterogeneous to reflect operational linkages among proximate projects. In contrast, a buffer yields a location-centered and symmetrical definition of local exposure, ensuring that two projects at the same distance from a given site are treated equally regardless of their absolute position on a grid.



(a) Pre-2010 and 2010 World Bank project locations in Ghana

(b) Illustration of the spatial matching and counting procedure

Figure 1: Spatial Matching Approach

Notes: Figure 1a displays pre-2010 and 2010 World Bank project locations in Ghana, with 25km buffers drawn around focal projects approved in 2010. The dashed bounding box in Figure 1a indicates the area enlarged in Figure 1b. The zoomed-in panel illustrates how prior projects located within the buffer are identified and counted. Only projects completed before the start date of the focal project are considered when constructing measures of local aid exposure.

focal project captures the set of nearby previously completed activities, representing the accumulated local experience from which implementing teams and institutions may have learned. These indicators reflect the stock of localized implementation knowledge and institutional capacity that can shape the performance of subsequent projects. In addition, to account for contemporaneous factors that could confound the estimated learning effects, I compute the mean values of relevant covariates such as local socioeconomic indicators, conflict incidence and weather characteristics over the duration of each project. This approach approximates a counterfactual environment, ensuring that observed associations between prior project performance and current outcomes are not merely driven by time-varying local conditions that simultaneously affect aid effectiveness.

Sample Processing: To construct the estimation sample, I apply a series of data quality filters. The analysis is restricted to projects with valid longitudinal coordinates that were geocoded with exact coordinates or assigned to a location verified to be within 25km of the correct location (i.e. precision code less than 4) (AidData, 2017; Bitzer & Gören, 2024; Briggs, 2018). Figure A.1 shows the geocoded aid locations with precision codes less than 4 between 1995 to 2014. Projects with implausible or inconsistent

dates such as those ending before they begin or lacking completion dates are removed to ensure accurate sequencing of prior projects. I also retain only projects with evaluation dates on or after completion, thereby excluding interim assessments that may induce anticipation effects. When there are multiple evaluations, only the final evaluation and corresponding score are kept. Furthermore, if ratings differ between AidData and IEG data, I keep the ratings from IEG, since these are constantly updated and represent recent data.

After these restrictions, the sample comprises 9,470 project locations out of the original 11,432 in the AidData dataset. Although this represents a substantial reduction, these filters isolate projects consistent with the identification strategy. The final regression sample contains 8,439 observations, as singleton groups within ADM_2 and TTL fixed-effects (FE) are excluded since they do not contribute to within-group identification (see Section 4).

Descriptive Statistics: Using each project’s geographic coordinates, I link information on prior local aid exposure and contextual geographic variables for all projects implemented. Table A.1 shows descriptive statistics of the main variables (based on the 25km buffer sample).

In Panel A, the main dependent variable is a binary indicator equal to 1 if a project receives an HS rating. Approximately 44 percent of projects are rated HS, while around 50% of project locations have at least one prior HS-rated project. Figure 2 below illustrates the distribution of evaluation outcomes over time. MS projects constitute the majority in most years, while HS and LS projects represent smaller but relatively stable shares.

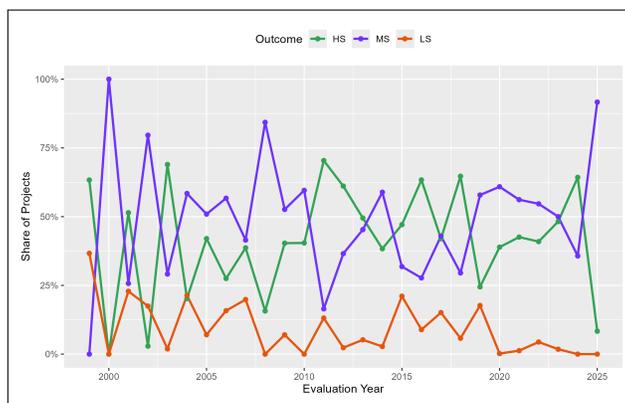


Figure 2: Project Success Shares over Time

Notes: Figure 2 illustrates the temporal evolution of project evaluation success over time. The figures are based on 25km buffer sample.

4 Empirical Strategy

Baseline Model The purpose of the baseline specification is to establish whether exposure to successful nearby projects increases the likelihood that a new project in the same area will also achieve a strong performance rating. The dependent variable, HS , equals 1 if a project receives a highly satisfactory rating and 0 otherwise. This binary measure focuses on projects that reach the highest standard of implementation quality and development outcomes, allowing the analysis to capture the mechanisms behind exceptional performance rather than average results. Similar outcome definitions are standard in empirical assessments of project effectiveness (Bulman et al., 2015; Denizer et al., 2013).

The main explanatory variable is the number of prior projects within a 25km radius that received HS, MS, or LS ratings before the start year of the current project. The 25km buffer represents a practical catchment area where project teams, contractors, and institutions can plausibly exchange information or resources. Using a smaller radius may overlook relevant local interactions, while a larger one could mix projects that operate under entirely different conditions. Robustness checks with 5–50km buffers confirm that the estimates are stable.

The analysis begins with the following baseline specification using a linear fixed-effects (OLS) model:

$$HS_{lct} = \beta_1 HS_{lct}^p + \beta_2 MS_{lct}^p + \beta_3 LS_{lct}^p + \delta \mathbf{X}'_{lct} + \rho_r + \lambda_t + \theta_s + \eta_k + \varepsilon_{lct} \quad (1)$$

where HS is the future focal project in location l , country c , evaluated in time t . Prior aid $p = \{dummy, counts\}$. Total counts are defined in two ways: (i) normal counts, referring to the total number of prior World Bank projects of a given outcome category (HS, MS, or LS) implemented within a 25km buffer before the start of the current project, counting all individual projects regardless of multiple projects of the same type, and (ii) unique counts, which is the number of distinct prior projects of each outcome category within the same 25km buffer, where multiple projects of the same type in the same location are counted only once, to avoid overrepresenting repeated operations in the same area. I use normal counts as the baseline to capture local aid intensity, that is, the full variation in aid exposure. The vector \mathbf{X}' contains controls for the average local population density, nighttime light intensity, accessibility, conflict incidence, and climatic conditions (precipitation, temperature, and drought) over the duration of current focal HS aid. ADM₂ region (ρ_r), evaluation year (λ_t), sector (θ_s) and TTL (η) capture unobserved differences in geography, time, and managerial or institutional quality. The parameter of interest, β_1 to β_3 , measures how an additional nearby prior HS project, for instance, affects the probability that the next project achieves an HS outcome. A positive and statistically significant estimate would suggest the presence of local learning or performance spillovers. This implies that project knowledge, management experience,

or institutional practices are transmitted across projects operating in close proximity. Standard errors are clustered by project to allow for within-project correlation. This is appropriate when a project covers multiple sublocations and might share the same design. Results are robust to alternative clustering and to models that use unique counts of prior projects.

5 Main Results

Table 1: Effect of Prior Project on Current Project Outcome

	(1)	(2)	(3)	(4)	(5)	(6)
	Dependent Variable: Current HS Project					
No. Prior HS projects	-0.0098 (0.0075)	-0.0183** (0.0073)	-0.0188** (0.0074)	-0.0173** (0.0076)	-0.0174** (0.0076)	-0.0193** (0.0075)
No. Prior MS projects		0.0125** (0.0053)	0.0117** (0.0055)	0.0123** (0.0055)	0.0125** (0.0057)	0.0121** (0.0056)
No. Prior LS projects			0.0197 (0.0132)	0.0218* (0.0132)	0.0222* (0.0134)	0.0205 (0.0135)
Number of projects	632	632	632	632	632	632
Observations	8,439	8,439	8,439	8,439	8,439	8,439
Within adjusted R ²	0.00175	0.00835	0.00875	0.00898	0.00894	0.01524
Dependent variable mean	0.44259	0.44259	0.44259	0.44259	0.44259	0.44259
Population & conflict controls	No	No	No	Yes	Yes	Yes
Nighttime & travel time controls	No	No	No	No	Yes	Yes
Weather controls	No	No	No	No	No	Yes
ADM ₂ FE	Yes	Yes	Yes	Yes	Yes	Yes
Evaluation year FE	Yes	Yes	Yes	Yes	Yes	Yes
TTL FE	Yes	Yes	Yes	Yes	Yes	Yes
Sector FE	Yes	Yes	Yes	Yes	Yes	Yes

Notes: The table reports coefficients from FE regressions of project success (a binary indicator equal to 1 if the project is rated Highly Satisfactory) on measures of prior local project experience within a 25km buffer. Columns (1) to (6) use counts of prior projects rated HS, MS, or LS, respectively. All models include second-order administrative division (ADM₂), evaluation year, team leader (TTL), and sector FE and control for average local population density, conflict incidence, nighttime lights, travel time, precipitation, temperature, and drought during the duration of project. Standard errors are clustered by project ID. *Significance codes:* ***: 0.01, **: 0.05, *: 0.1.

5.1 Baseline Results: Local Learning and Project Performance

Table 1 presents the baseline estimates examining how prior local project exposure relates to the probability of a subsequent project achieving an HS rating. Across all specifications, the dependent variable is a binary indicator equal to one for HS-rated projects. The models progressively add controls for other project types, local socioeconomic factors, and environmental conditions, while accounting for ADM₂, evaluation year, team leader (TTL), and sector FE. Column (1) considers only the count of prior HS projects within a 25km buffer around each project’s location. The coefficient on number of prior HS projects is negative, though not yet statistically significant, implying that additional successful projects nearby are not necessarily associated with higher chances of success for subsequent ones.

At face value, this result contradicts the concept of positive spatial learning externalities, or the expectation that nearby successful projects should promote local learning and institutional spillovers. Rather, it suggests that the benefits of previous high-quality interventions may diminish over time or even crowd out later initiatives. While this mechanism is conceptually plausible and consistent with broader organizational learning theories (Argote et al., 1990; Arrow, 1962; Benkard, 2000), it is not explicitly tested in Denizer et al. (2013). Instead, Denizer et al. (2013) show that “repeater” projects do not systematically perform better, indicating limits to the assumption that experience always improves outcomes.

When prior MS projects are added in Column (2), the relationship between prior HS projects and current outcomes becomes both larger in magnitude and statistically significant at the 5% level. The coefficient of -0.0183 suggests that, conditional on past exposure to MS projects, each additional past HS project within 25km is associated with roughly a 1.8-percentage-point reduction in the probability of current project success. Conversely, the positive and significant coefficient on prior MS projects indicates that moderately successful past interventions may contribute to incremental improvements in future project outcomes. This suggests that even projects that fall short of a top HS rating may still provide useful managerial or procedural knowledge.

Column (3) introduces prior LS projects. The coefficient on prior HS exposure remains negative and significant, while prior LS projects are statistically insignificant. This pattern supports the theory that failure does not systematically propagate across space, suggesting that weakly performing projects may provide fewer observable lessons to neighboring interventions. In contrast, successful projects might shape expectations, alter resource allocation, or attract more complex follow-up interventions that carry higher risk, producing the observed negative association.

Columns (4) to (6) progressively add controls for average population density, conflict incidence, night-time lights (as a proxy for local economic activity), travel time to cities, precipitation, temperature and drought severity. Despite these additional controls, the main coefficients of interest remain remarkably stable. The stability of these coefficients across specifications suggests that the results are not driven by local confounding factors, such as differences in accessibility, exposure to shocks, or underlying economic conditions. This reinforces the interpretation that the patterns observed reflect localized learning dynamics and diminishing returns on concentrated prior success.

The magnitudes imply that, holding other factors constant, each additional HS-rated project implemented nearby reduces the likelihood of a subsequent project achieving an HS rating by roughly 1 to 2 percentage points, whereas each additional MS-rated project increases it by about 1 percentage point. Given that the mean of the dependent variable is 0.44, these effects are economically meaningful.

The negative marginal effect of additional nearby HS-rated projects can be interpreted in light of the World Bank’s assessment of project success. As emphasized by Bulman et al. (2015) and Denizer et al. (2013), outcome ratings are explicitly benchmarked against each project’s own development objective rather than a fixed standard. This is because objectives evolve as the local portfolio matures, often becoming broader or more ambitious, and may later face systematically tougher benchmarks. Moreover, as they document project development, monitoring systems flag difficulties relative to the stated objective, and these flags are closely tied to the ultimate rating. Overall, this implies that in areas with a history of HS projects, subsequent interventions may be evaluated against more demanding objectives, making HS ratings progressively harder to achieve. This mechanism provides a natural explanation for the small but meaningful decline (about 1 to 2 percentage points) in HS likelihood associated with each additional past HS project in the vicinity.

In sum, Table 1 provides compelling baseline evidence that the relationship between prior aid performance and current project outcomes is not uniformly positive. While prior moderate success appears to promote incremental learning and improved performance, too much prior success may generate complacency, resource reallocation, or complexity spillovers that reduce the probability of current project success. This non-linear pattern is consistent with the theory that aid effectiveness depends not only on learning from success but also on the capacity to absorb and sustain it locally. These findings are similar when using unique counts (see Appendix Table A.2)

5.2 Interaction Effects:

Table 2 examines whether the relationship between prior project exposure and current project performance depends on how we measure prior experience and on the coexistence of projects of different quality ratings. The dependent variable remains a binary indicator for projects rated HS. Column (1) replaces project counts with binary indicators that equal 1 if any prior project HS, MS, or LS was implemented within the 25km buffer before the start of the current project. This specification primarily serves as a robustness check to determine whether results are sensitive to the functional form of the exposure measure. The results show that the presence (not the count) of a prior HS project is negatively associated with the likelihood of achieving future HS outcomes, whereas prior MS and LS exposure are positively and significantly associated, respectively. This suggests that the baseline negative spillovers from prior HS and positive effects from moderate success do not depend on whether exposure is measured in counts or a simple indicator. In other words, even the presence of a nearby high-performing project is associated with a small reduction in subsequent success, while moderate quality exposure continues to have a beneficial impact. The stability of these coefficients confirms that the negative effect associated with prior HS is

Table 2: Interaction Effects of Prior Project Exposure

	(1)	(2)	(3)
	Dependent Variable: Current HS projects		
	Indicator	Baseline: Normal Counts	Interactions
Prior HS projects	-0.1066*** (0.0344)	-0.0193** (0.0075)	-0.0295*** (0.0103)
Prior MS projects	0.0493* (0.0288)	0.0121** (0.0056)	0.0101 (0.0070)
Prior LS projects	0.0586** (0.0260)	0.0205 (0.0135)	0.0353* (0.0181)
Prior HS × Prior MS			0.0010** (0.0005)
Prior HS × Prior LS			0.0006 (0.0056)
Prior MS × Prior LS			-0.0025 (0.0019)
Observations	8,439	8,439	8,439
Within adjusted R ²	0.01524	0.01538	0.01867
Baseline controls	Yes	Yes	Yes
ADM ₂ FE	Yes	Yes	Yes
Evaluation year FE	Yes	Yes	Yes
TTL FE	Yes	Yes	Yes
Sector FE	Yes	Yes	Yes

Notes: : This table examines whether the relationship between prior local project exposure and project performance varies across types of prior projects. Column (1) use binary indicators to show whether any prior project of each type (HS/MS/LS) was implemented within 25km before the project's start date. Column (2) replaces these with the corresponding counts of prior projects (**Baseline results from Table 1**). Column (3) reports interaction terms between prior HS, MS, and LS project counts to test whether the coexistence of different-quality prior projects. All models include ADM₂, evaluation year, TTL, and sector FE and control for average local population density, conflict incidence, nighttime lights, travel time, precipitation, temperature, and drought during the duration of a project. Standard errors are clustered by project ID. *Significance codes:* ***: 0.01, **: 0.05, *: 0.1.

not an artifact in the exposure measure. This robustness to specification choice increases confidence in the interpretation that the relationship between local learning and aid performance follows a diminishing pattern. Column (2) reinstates the count-based measure and thus represents the baseline specification in Table 1.

Column (3) introduces interaction terms between prior HS, MS, and LS project counts from Equation 2 to explore whether past different-quality project outcomes affect the probability of having an HS. The coefficient on prior HS becomes slightly larger in magnitude (-0.0295, significant at the 1% level), implying that, on average, an additional HS project is associated with a 3-percentage-point decline in the probability of current success given no prior projects. However, the positive and significant interaction term between HS and MS projects (0.0010) indicates that this negative effect is partially offset in areas where both HS and MS projects have previously been implemented. This means that when prior experience includes a

mix of highly and moderately successful projects, the negative externality of HS concentration weakens. This is consistent with the theory that diversity in prior project quality promotes adaptive learning. Interactions involving LS projects remain statistically insignificant, suggesting that very low-quality prior experiences contribute little to local institutional learning.

Table 3: Marginal Effects – Interactions

(1) Prior HS	(2) Prior MS	(3) Prior LS	(4) Freq.	(5) Freq. (%)	(6) Marginal Effects		
					HS	MS	LS
0	1	0	448	15.88	–	0.010	–
1	0	0	334	11.84	-0.030	–	–
0	2	0	196	6.95	–	0.010	–
0	0	1	139	4.93	–	–	0.035
1	1	0	123	4.36	-0.029	0.011	–
0	3	0	101	3.58	–	0.010	–
2	0	0	97	3.44	-0.030	–	–
2	1	0	57	2.02	-0.029	0.012	–
1	2	0	52	1.84	-0.027	0.011	–
0	4	0	47	1.67	–	0.010	–
0	1	1	44	1.56	–	0.010	0.035
2	2	0	36	1.28	-0.027	0.012	–
0	2	1	35	1.24	–	0.010	0.035
1	0	1	33	1.17	-0.030	–	0.035
3	0	0	33	1.17	-0.030	–	–
3	1	0	33	1.17	-0.029	0.013	–
2	3	0	30	1.06	-0.026	0.012	–
1	3	0	29	1.03	-0.026	0.011	–
1	2	1	27	0.96	-0.027	0.011	0.035
0	3	1	26	0.92	–	0.010	0.035

Notes: This report analyzes marginal effects for project combinations appearing with $\geq 1\%$ frequency (268 unique combinations) for project counts. Columns (1) to (4) present project quality combinations, whereas columns (4) to (5) show raw counts and percentages of these combinations in the sample. Columns (6) to (8) display marginal effects calculated using Equations (3), (4) and (5) and coefficients from Table 2, column (3). For example, for a single HS project, substituting $MS_{lct} = 0$ and $LS_{lct} = 0$ into $-0.0295 - 0.0010 \times MS_{lct} - 0 \times LS_{lct}$ yields -0.030 percentage points. Insignificant coefficients are treated as 0. Bold values are mentioned in the paper. Calculations use maximum decimals and are rounded to three decimal places.

To illustrate these interaction dynamics more accurately, Table 3 reports marginal effects derived from the interaction model in Equation 2 (see the Appendix for marginal equations (3), (4), (5) and coefficients from Column 3 of Table 2), weighted by the observed frequency of each project-quality combination in the estimation sample. This makes it possible to translate the regression coefficients into realistic scenario-based effects depending on how often different combinations occur in practice. For locations with only prior HS projects (e.g., 1-0-0 or 2-0-0), the marginal effect remains around -0.03, implying a 3-percentage-point decline in HS outcomes for each additional prior HS project. These scenarios represent approximately 12–13% of the estimation sample, indicating that a localized concentration of high-performing projects is relatively common and systematically linked to reduced marginal performance. Areas with only MS

projects (e.g., 0-1-0 or 0-2-0) experience marginal effects of +0.01 per additional project. Though small in magnitude, these gains are consistent across exposure levels, reinforcing the idea that incremental learning from moderate success is persistent and beneficial. In areas with a combination of HS and MS projects (e.g., 1-1-0 or 2-1-0), the marginal effect of HS exposure becomes less negative -0.029 (although very small). This suggests that coexposure to moderately successful projects reduce the negative impact of HS concentration. The inclusion of LS projects in the mix (e.g., 0-1-1 or 1-0-1) slightly raises predicted success probabilities for prior LS (0.035), but has neutral effects for interactions between HS (-0.030) or MS (0.010). These effects are statistically significantly different from 0, aligning with the regression results above.

These marginal effects confirm that the net effect of prior aid exposure depends not only on its quantity but also on its qualitative composition. Local areas that have previously hosted both high- and moderately performing projects appear to sustain better subsequent outcomes, possibly due to diversified implementation experience and cross-learning among project teams and institutions.

Conversely, environments saturated with high-performing projects might face “learning exhaustion,” where marginal improvements become harder to achieve. This pattern echoes the finding that localized aid learning exposure promotes adaptation, but excessive repetition of “best practices” may lead to rigidity and reduce innovation.

6 Mechanisms

6.1 TTL Characteristics

Table 4 examines whether the negative relationship between previous exposure to HS projects and project performance can be explained by differences in TTL quality and experience. This analysis directly addresses one of the key findings of the baseline results: if prior exposure to HS projects is a measure of learning-by-doing or better manager quality, why does it correlate with lower performance in subsequent projects? The analysis includes controls and interaction terms to find two main aspects of managerial capacity. TTL quality is defined as the average share of HS outcomes across all projects previously managed by a given TTL, capturing persistent differences in managerial competence. TTL experience is measured as the number of projects handled before the current one, regardless of performance ratings obtained by a given TTL over the years.

Column (1) includes a direct control for TTL quality. TTL quality shows a positive and significant predictor of project success, indicating that projects led by higher-quality TTLs are more likely to achieve HS ratings. This result confirms the economic relevance of the quality measure and is consistent with

established evidence that managerial ability is critical for project outcomes (Bulman et al., 2016; Denizer et al., 2013; Moll et al., 2015). However, the coefficient on prior HS exposure remains negative and statistically significant after controlling for TTL quality. This suggests that the baseline result is not attributable to weaker leaders being disproportionately associated with repeated HS exposure.

Table 4: Mechanisms – TTL characteristics

	(1)	(2)	(3)	(4)	(5)	(6)
	Dependent Variable: Current HS project					
	TTL Q. controlled	TTL Q. interacted	TTL Exp. controlled	TTL Exp. interacted	TTL Q. and Exp. controlled	TTL Q. and Exp. interacted
Prior HS projects	-0.0214*** (0.0082)	-0.0184** (0.0094)	-0.0415*** (0.0116)	-0.0235 (0.0216)	-0.0213*** (0.0082)	-0.0215*** (0.0082)
Prior MS projects	0.0106** (0.0049)	0.0106** (0.0049)	0.0226*** (0.0063)	0.0233*** (0.0062)	0.0107** (0.0049)	0.0110** (0.0049)
Prior LS projects	0.0168 (0.0173)	0.0167 (0.0173)	0.0501* (0.0267)	0.0496* (0.0269)	0.0167 (0.0173)	0.0161 (0.0172)
TTL Quality	1.044*** (0.0292)	1.046*** (0.0295)			1.046*** (0.0292)	1.056*** (0.0369)
Prior HS projects × TTL quality		-0.0062 (0.0125)				
TTL experience			3.13×10^{-5} (3.45×10^{-5})	3.51×10^{-5} (3.43×10^{-5})	-1.02×10^{-5} (2.3×10^{-5})	9.83×10^{-5} (0.0004)
Prior HS projects × TTL experience				-5.35×10^{-6} (5.1×10^{-6})		
TTL (quality × experience)						-0.0002 (0.0007)
Observations	8,481	8,481	8,481	8,481	8,481	8,481
Within adjusted R ²	0.47701	0.47697	0.02760	0.02890	0.47714	0.47713
Baseline controls	Yes	Yes	Yes	Yes	Yes	Yes
ADM ₂ FE	Yes	Yes	Yes	Yes	Yes	Yes
Evaluation year FE	Yes	Yes	Yes	Yes	Yes	Yes
TTL FE	No	No	No	No	No	No
Sector FE	Yes	Yes	Yes	Yes	Yes	Yes

Notes: This table examines potential mechanisms through which prior project exposure affects project performance, focusing on team leader (TTL) quality and experience. The dependent variable is a binary indicator equal to 1 for projects rated HS. All models include ADM₂, evaluation year and sector FE, and control for average local population density, conflict incidence, nighttime lights, travel time, precipitation, temperature, and drought during the duration of project. Standard errors are clustered by project ID. *Significance codes:* ***, 0.01, **, 0.05, *, 0.1.

Column (2) introduces an interaction between prior HS exposure and TTL quality to determine whether very good team leaders can avoid the downside of having worked on many successful projects before. That is, if there is a negative effect of prior success because weaker leaders get stretched too thin or perform worse over time, then strong leaders should be able to handle it better. The results show that this is in fact not the case. The interaction term that measures whether high-quality TTLs weaken the negative effect is not statistically significant. In simple terms, even leaders with strong past performance still see their projects perform worse when the location has had a lot of prior HS projects. One important factor that the evidence points to is that the negative relationship is unlikely to come from individual leader problems such as poor effort, fatigue, or lack of skill. Instead, it points to broader constraints, such as limits in the local environment or diminishing gains from repeating similar projects that even good leaders cannot easily overcome.

Columns (3) and (4) focus on managerial experience. Although experience may serve as a proxy for familiarity with institutional processes, implementation challenges, or stakeholder coordination, its standalone effect is weak and statistically insignificant. Experience does not meaningfully interact with prior HS exposure either. These findings are similar to Moll et al. (2015) and indicate that accumulating additional project cycles does not systematically increase the likelihood of achieving HS outcomes or mitigate the negative effects associated with repeated HS exposure. In summary, both results distinguish competence from exposure. In other words, while quality is important, experience alone does not appear to drive marginal performance.

Columns (5) and (6) account for both TTL quality and experience, with and without interaction terms, respectively. The results remain stable; TTL quality continues to have a strong positive effect, while prior HS exposure remains negatively and statistically significantly associated with current success. Neither experience nor the interaction between quality and experience meaningfully alters this relationship. The consistency of coefficients across specifications supports the interpretation that the negative effect of prior HS exposure is not an artifact of omitted managerial characteristics.

Appendix Table A.3 further supports this conclusion by restricting the sample to projects with fully observed TTL information. The persistence of the main results in this restricted sample addresses concerns that missing leader data affects the findings. TTL quality remains a strong predictor of success, while prior HS exposure continues to exhibit a negative association, confirming that the mechanism results are robust to sample composition.

Overall, the results highlight that effective leadership improves project outcomes but does not change the negative effect associated with concentrated prior exposure to HS projects. This pattern holds even for projects managed by highly capable and experienced TTLs, indicating that the observed decline is unlikely to stem from individual managerial limitations. Instead, it points to broader contextual constraints, such as saturation effects, institutional limits, or reduced marginal returns from repeated interventions.

6.2 Funding volume

Table 5 Column (1) shows whether the negative association between prior exposure to HS projects can be attributed to differences in funding intensity. Consistent with standard theories of project implementation, funding volume is positively and statistically significantly associated with project success. Better-funded projects are more likely to achieve HS ratings, reflecting the role of financial resources in easing implementation constraints, enabling adequate staffing and supervision, and allowing greater flexibility in responding to operational challenges. This finding aligns with Denizer et al. (2013) showing that funding adequacy is a key determinant of project performance.

However, the interaction between prior HS exposure and funding volume in Column (2) is small and statistically insignificant. This indicates that increased funding does not mitigate the negative relationship between prior HS exposure and current project success. In other words, while funding improves outcomes on average, it does not alter the way past success translates into future performance. If the observed diminishing returns on prior HS exposure were primarily driven by financial constraints such as declining budgets, cost overruns, or underfunding of follow-up projects, higher funding levels would be expected to weaken or reverse the negative effect. The absence of such moderation effects provides strong evidence against this intuition. Instead, the persistence of the negative association even after controlling for funding

Table 5: Mechanisms – Funding

	(1)	(2)
	Dependent Variable: Current HS projects	
	Funding: controlled	Funding: interacted
Prior HS projects	-0.0151** (0.0070)	-0.0218** (0.0099)
Prior MS projects	0.0117** (0.0054)	0.0122** (0.0055)
Prior LS projects	0.0206 (0.0137)	0.0193 (0.0139)
ln (1 + disbursement)	0.0128** (0.0059)	0.0115* (0.0062)
Prior HS projects × ln (1 + disbursement)		0.0011 (0.0007)
Observations	8,439	8,439
Within adjusted R ²	0.03140	0.03309
Baseline controls	Yes	Yes
ADM ₂ FE	Yes	Yes
Evaluation year FE	Yes	Yes
TTL FE	No	No
Sector FE	Yes	Yes

Notes: This table investigates potential mechanisms through which prior project exposure affects project performance, focusing on funding volume. The dependent variable is a binary indicator equal to one for projects rated HS. All models include ADM₂, evaluation year, TTL and sector FE and control for average local population density, conflict incidence, nighttime lights, travel time, precipitation, temperature and drought during the duration of project. Standard errors are clustered by project ID. *Significance codes:* ***: 0.01, **: 0.05, *: 0.1

volume suggests that the mechanism operates using channels through which additional financial resources alone cannot resolve project complexities in a given location.

7 Robustness Checks

7.1 Robustness to Spatial Definition – Buffer Sizes

Figure 3 also shows how the estimated effects of prior project exposure change as we vary the spatial distance, using buffer radii from 5–50km. Examining this sensitivity is essential because the relevant geographical scope of learning, congestion, or institutional spillovers is not known ex ante. If the results were driven by an arbitrary choice of distance, the estimated coefficients would be expected to fluctuate substantially as the buffer size changes.

For prior HS projects, the figure shows a consistently negative coefficient across almost all buffer sizes. The effect is pronounced at relatively short distances, roughly 5–25km. This is the range where projects are most likely to share the same local institutions, implementation capacity, and beneficiaries. As the buffer increases, the negative effect gradually weakens, indicating that projects further away matter less in shaping the local environment for future projects. Nevertheless, the effect remains negative even at larger distances, reinforcing the theory that the relationship is not sensitive to a particular cutoff but

reflects genuinely local dynamics.

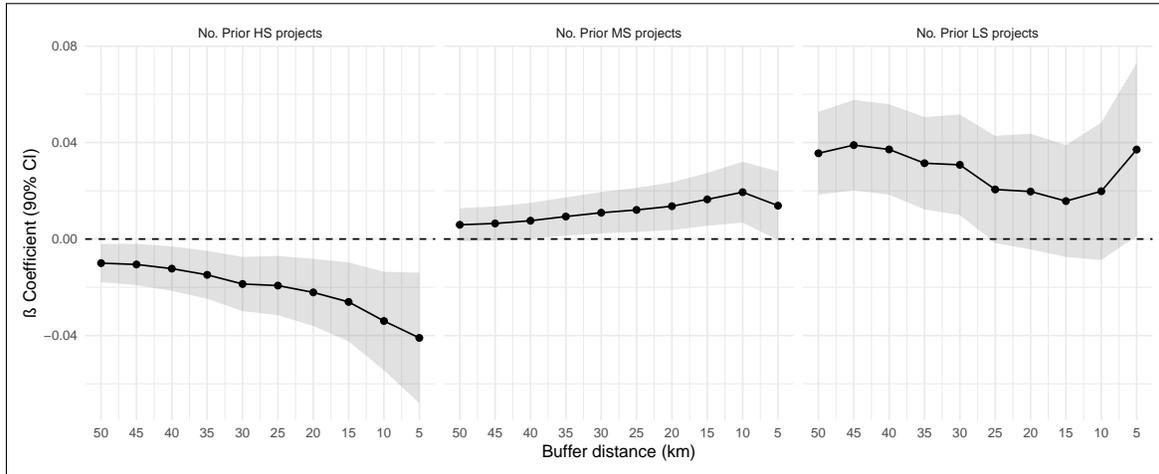


Figure 3: Sensitivity of Prior Project Effects to Spatial Buffer Size

Notes: This figure tests the robustness of the estimated relationship between prior project exposure and current project performance to alternative spatial definitions of local exposure. It plots the estimated coefficient of the number of prior HS, MS, or LS projects (each point represents the coefficient estimate) on current HS-rated projects for different spatial buffer sizes (5-50 km) around each project’s location centroid. The shaded areas show 90% confidence intervals. All models include the full set of controls and FE as in the baseline specification (25km buffer).

In contrast, prior MS projects exhibit a small but positive association with current project success that is relatively stable across buffer sizes. The gradual change in the coefficient as the buffer expands suggests that MS projects may generate broader, more diffuse benefits such as incremental learning that extend beyond very narrow geographic areas. Unlike HS exposure, MS exposure does not appear to generate congestion or saturation effects, even at smaller distances.

For prior LS projects, at smaller buffer sizes, the coefficients are close to 0 and statistically insignificant, suggesting that LS projects do not have strong, localized effects on nearby subsequent projects. However, as the buffer expands, the coefficients become larger and statistically significant. This indicates that the influence of LS projects operates at a broader spatial scale, potentially reflecting region-wide factors such as persistent institutional weaknesses, unfavorable implementation environments, or structural constraints that are shared across larger areas rather than confined to immediate project neighborhoods. Here, LS exposure appears to be less about local spillovers and more about broader contextual conditions that only become visible when exposure is measured over a wider geographical scope.

In sum, the shape of the estimates across buffer sizes is informative. The fact that the negative effect of prior HS exposure is strongest at short distances and fades consistently as distance increases is exactly what is to be expected if the mechanism operates through local saturation or capacity constraints. At the same time, the stability of the results across a wide range of spatial definitions provides reassurance

that the main findings are not driven by arbitrary geographic choices, but instead capture robust effects between past performance and current project outcomes.

7.2 Alternative Dependent Variable Specifications:

Table 6: Alternative Dependent Variable

	(1) Outcome: MS	(2) Outcome: LS
No. Prior HS projects	0.0141* (0.0080)	0.0052 (0.0037)
No. Prior MS projects	-0.0101* (0.0060)	-0.0020 (0.0022)
No. Prior LS projects	-0.0068 (0.0136)	-0.0138 (0.0113)
Observations	8,439	8,439
Within adjusted R ²	0.01177	0.00268
Baseline controls	Yes	Yes
ADM ₂ FE	Yes	Yes
Evaluation year FE	Yes	Yes
TTL FE	Yes	Yes
Sector FE	Yes	Yes

Notes: The table presents FE estimates of the relationship between prior project exposure and various project success outcomes. The key independent variables measure the number of prior HS, MS, and LS projects within a 25km buffer before project start. Dependent variables differ across columns: Column (1): MS dummy (1 if IEG rating = MS); Column (2): LS dummy (1 if IEG rating = LS). All regressions include multiple FE (region, year, TTL, and sector) and the full set of baseline controls. Clustered standard errors (by project ID) are reported in parentheses. *Significance codes:* ***: 0.01, **: 0.05, *: 0.1

Table 6 further checks the robustness of the main results by redefining the dependent variable. Instead of focusing on whether a project achieves a HS rating, the same specification is estimated using MS and LS outcomes. This analysis helps clarify where in the performance distribution the baseline effect is operating.

The results are fully consistent with the patterns documented earlier in the paper. Prior exposure to HS projects is not associated with a higher likelihood of lower performance. Rather, its effect shows up as a shift from HS to MS outcomes. When MS is used as the dependent variable, prior HS exposure is weakly positively associated with the probability of achieving an MS rating, while no meaningful relationship emerges for LS outcomes. This mirrors the main findings, which suggest that repeated local success makes it harder to sustain top-tier performance, but does not push projects toward poor outcomes.

At the same time, prior exposure to MS and LS projects exhibits small and mostly insignificant

coefficients across alternative outcome definitions, indicating limited spillover effects from low performing projects. These results reinforce the interpretation that the central dynamic identified in the paper operates specifically at the top of the performance distribution. The trade-off is between exceptional and good performance (HS versus MS), not between success and failure. Therefore, the robustness check confirms that this pattern is not driven by how project outcomes are defined.

7.3 Estimation method:

Table A.4 uses a logit estimator to assess the robustness of the baseline findings. It contrasts specifications that use binary indicators of prior exposure (equal to 1 if there was any HS/MS/LS project within 25km before the start date) with those using count-based measures that capture the intensity of prior activity. Across all columns, the coefficient on prior HS projects remains negative and statistically significant, confirming that the adverse association between prior local success and current project performance is robust to both the definition of exposure and the underlying model estimator. This pattern supports the interpretation of diminishing marginal returns of repeated HS projects within the same geographic area, as previously indicated in the baseline results. The coefficients on prior MS and LS projects are insignificant, suggesting that exposure to moderately or poorly performing projects may not generate learning or adaptive effects that fully translate into improved outcomes.

Overall, the consistency of the results across binary versus count measures and logit models strengthens the empirical credibility of the main findings. It suggests that the negative relationship observed between prior HS exposure and current performance is not as a result of the estimator, but a stable feature of how project experience and concentration shape aid effectiveness.

Clustering: Table A.5 evaluates whether the baseline results are sensitive to the choice of clustering level for standard errors. Columns (1) to (3) replicate the main specification using three clustering strategies: by project, by ADM₂ and two-way clustering by both project and region. The estimated coefficients remain identical across all specifications, both in magnitude and statistical significance. The effect of prior HS project exposure remains negative and significant, while prior MS exposure retains a positive and significant association with subsequent performance. This stability demonstrates that the results are not driven by spatially correlated shocks or serial correlation within projects and that the inference is robust to different assumptions about the underlying error structure.

This finding increases confidence in the main estimates by showing that statistical precision and coefficient signs are unaffected by how residual dependencies are handled, indicating that the observed relationships reflect substantive project dynamics.

8 Discussion

Aid effectiveness in African countries has been widely linked to both macro-level institutional conditions and project-level characteristics. Research to date highlights the importance of governance quality, national institutions, and managerial capacity in shaping development outcomes (Ashton et al., 2022; Bulman et al., 2016; Dalgaard et al., 2004; Denizer et al., 2013; Temple, 2010; Winters, 2019). Building on this literature, the present paper introduces a complementary perspective by asking whether the local history of project performance itself affects subsequent outcomes. While it is often assumed that past success should generate positive spillovers through institutional learning, familiarity with local systems, or improved coordination among stakeholders, the evidence presented here suggests that the relationship between prior local success and future performance is more nuanced.

The key findings of the paper suggest that repeated exposure to highly successful projects is associated with a lower probability of achieving another top rating in the same locality (see Table 1). Rather than generating cumulative gains, prior success is associated with declining marginal performance. This pattern suggests localized diminishing returns to repeated excellence, consistent with broader discussions of absorptive-capacity limits and diminishing marginal productivity in aid contexts (Dalgaard et al., 2004; Feeny & de Silva, 2012; Radelet, 2026). Sustaining very high performance may therefore become increasingly difficult once the most accessible gains have already been realized.

At the same time, these findings partially contrast with the evidence from Denizer et al. (2013), who found that country-level governance and institutional quality were the dominant factors in explaining World Bank project outcomes. Whereas their results highlighted that “good countries make good projects,” the current evidence highlights the importance and limits of localized project spillovers within countries. The persistence of negative or neutral local effects, even after controlling for region, sector, and TTL fixed effects, indicates that prior micro-level project dynamics operate differently from macro-governance drivers. Rather than a simple accumulation of institutional capability, repeated success in the same locality may lead to complacency, resource saturation, or overextension of administrative capacity, dampening performance in subsequent interventions.

Moreover, this decline in performance cannot be attributed to weaker leadership (see Table 4, Column (1)). While higher-quality TTLs significantly improve project outcomes on average, consistent with evidence on the importance of managerial quality in development operations (Ashton et al., 2022; Bulman et al., 2016), stronger leadership does not offset the negative association linked to prior HS exposure (see Table 4, Column (2)). Similarly, managerial experience alone does not buffer the decline (Table 4, Column (4)), echoing findings in Moll et al. (2015) that managerial experience alone does not guarantee improved performance. These results indicate that the observed pattern is not driven by individual managerial

shortcomings, but by constraints operating at the local level that can affect even competent leaders.

Nor does the evidence point to declining financial resources as the primary explanation. Projects with greater funding capacity perform better overall (see Table 5, Column (1)), consistent with prior findings that resources are crucial to project success (Denizer et al., 2013), yet additional funding does not mitigate the negative impact of prior HS exposure (see Table 5, Column (2)). This suggests that the constraint is not simply financial. Even when resources align with project needs, they may not overcome deeper bottlenecks related to local absorptive capacity or administrative congestion. Thus, the findings align with broader arguments that increased aid or spending does not automatically translate into proportional performance gains once capacity limits are reached (Asare, 2025; Subramanian & Rajan, 2005). Moreover, implementation capability bottlenecks are not easily relaxed by additional funding alone (Pritchett et al., 2010, 2012).

In contrast, exposure to moderately successful projects is modestly associated with improved subsequent performance (see Table 1). Unlike concentrated HS exposure, MS experience does not exhibit signs of localized saturation. The spatial analysis shows that MS effects are weaker and less sharply concentrated at short distances (see Figure 3), suggesting that any learning generated by moderately successful projects is more diffuse and not tied to tight institutional bottlenecks. Rather than exhausting local capacity, MS exposure appears to support incremental adjustment. Projects that perform reasonably well, but not exceptionally, may leave space for reflection, adaptation, and refinement, instead of encouraging rigid replication of established approaches. This pattern is consistent with arguments in the development and public management literature that emphasize iterative learning and problem-driven adaptation as key to sustained improvement (Pritchett et al., 2010, 2012). Sustained performance, therefore, appears more likely in environments characterized by diverse experiences and continuous adjustment than in environments that rely repeatedly on the “best” methods when they are already excellent.

On the other hand, having unsatisfactory projects shows little systematic effect on subsequent outcomes. There is no evidence of strong corrective learning, nor of persistent negative spillovers. This suggests that very poor performance offers limited transferable learning and does not meaningfully shape subsequent project trajectories. This pattern is consistent with evidence that development organizations often struggle to learn systematically from sub-optimal performance (Independent Evaluation Group, 2014, 2022). IEG reports that the World Bank has no established mechanism for capturing and sharing lessons from dropped or poorly performing projects, which can limit organizational learning. Spatial effects, where present, appear only at larger buffer sizes (see Figure 3), suggesting that any association reflects broader contextual conditions rather than tightly localized dynamics. Most importantly, LS exposure does not increase the likelihood of subsequent low performance either (see Table 6), indicating

that poor past performance does not generate a self-reinforcing cycle of failure.

In conclusion, the results show that learning and performance in aid effectiveness are more complicated than they seem. Experience alone is insufficient to sustain high performance. Maintaining excellence appears to require fresh ideas, better oversight and adaptation to changing local conditions rather than relying solely on past success. In places that are already doing well, the main challenge is not just avoiding failure, but keeping up excellence after the easiest gains are achieved. An important avenue for future research is to examine whether these localized dynamics vary systematically across sectors, where implementation structures, capacity constraints, and learning processes may differ.

9 Conclusion

The present study contributes to the broader debate on what drives foreign aid or development effectiveness by shifting attention from cross-country institutional capacity to localized project histories. Using spatially defined project exposure measures and a range of robustness checks, the findings suggest that prior local success does not guarantee future excellence and may even reduce the likelihood of repeated high performance.

The evidence supports context-specific learning, where moderate successes encourage adaptation but repeated high performance risks diminishing marginal returns. TTL quality and project funding mechanisms appear to be an important aspect for project success, but they do not mediate prior HS effects. This highlights the importance of managerial oversight and incentive structures in sustaining project quality.

Overall, the results complement and extend earlier evidence from Ashton et al. (2022), Bulman et al. (2015), Denizer et al. (2013), and Moll et al. (2015) by revealing that, even within the same institutional setting, performance dynamics can vary widely across space and over time. These findings highlight that improving aid effectiveness requires not only good institutions and experienced managers but also mechanisms to preserve learning, accountability, and motivation after success. Sustained development performance depends less on repeating success and more on renewing learning processes in each local context.

The findings suggest several directions for future research. One potential research avenue is to explore how heterogeneity among team leaders in terms of their leadership styles, sector experience, or career paths may shape the way past project experience translates into future performance and whether the effects can be ascribed to individual managers rather than to learning or congestion within local institutions. In addition, building on recent studies of managerial rotation (Ashton et al., 2022), future research could look at how reassigning project leaders after successful interventions affects later performance and local learning. This approach would help clarify the relative roles of learning and saturation in shaping project

performance. Finally, extending the analysis to additional donors or institutional settings would also help assess the broader generality of the findings.

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Appendix

A Equations

The main equation of the interactions effect for the prior count is as follows:

$$\begin{aligned}
 HS_{ilct} = & \beta_1 HS_{lct}^p + \beta_2 MS_{lct}^p + \beta_3 LS_{lct}^p + \\
 & \beta_4 (HS_{lct}^p \times MS_{lct}^p) + \beta_5 (HS_{lct}^p \times LS_{lct}^p) + \beta_6 (MS_{lct}^p \times LS_{lct}^p) + \\
 & \delta \mathbf{X}'_{lct} + \rho_r + \lambda_t + \theta_s + \eta_k + \varepsilon_{lct}
 \end{aligned} \tag{2}$$

The corresponding marginal effect equations can be expressed as:

$$\frac{\partial HS_{ilct}}{\partial HS_{lct}^p} = \beta_1 + \beta_4 MS_{dct}^p + \beta_5 LS_{dct}^p \tag{3}$$

$$\frac{\partial HS_{ilct}}{\partial MS_{dct}^p} = \beta_2 + \beta_4 HS_{dct}^p + \beta_6 LS_{dct}^p \tag{4}$$

$$\frac{\partial HS_{ilct}}{\partial LS_{dct}^p} = \beta_3 + \beta_5 HS_{dct}^p + \beta_6 MS_{dct}^p \tag{5}$$

B Figures

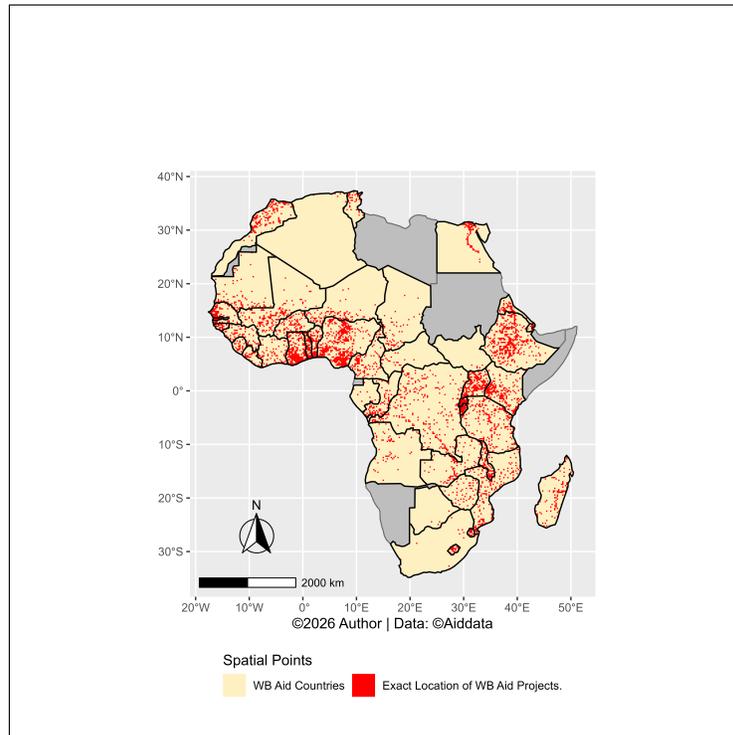


Figure A.1: Geo-Referenced Aid Locations in Africa

Notes: This figure shows World Bank-funded projects in Africa between 1995 to 2014.

C Tables

Table A.1: Descriptive Statistics

Statistics	Obs.	Mean	St. Dev.	Min	Max
<i>Panel A: Dependent variables</i>					
HS projects	8,439	0.443	0.497	0	1
MS projects	8,439	0.469	0.499	0	1
LS projects	8,439	0.088	0.284	0	1
<i>Panel B: Prior Aid Exposure (Normal Counts)</i>					
No. Prior HS projects	8,439	0.501	1.790	0	21
No. Prior MS projects	8,439	0.918	3.048	0	38
No. Prior LS projects	8,439	0.148	0.599	0	7
<i>Panel C: Prior Aid Exposure (Unique Counts)</i>					
No. Unique prior HS projects	8,439	0.301	0.804	0	11
No. Unique prior MS projects	8,439	0.461	1.023	0	8
No. Unique prior LS projects	8,439	0.103	0.323	0	2
<i>Panel D: Funding (in \$)</i>					
Total commitments	8,439	94,267,441	127,153,835	0	3,829,940,940
Total disbursements	8,439	56,160,127	96,206,040	0	898,173,587
Even split commitments	8,439	4,307,040	15,217,872	0	612,790,550
Even split disbursements	8,439	2,267,264	5,672,736	0	217,027,052
<i>Panel E: Geographic Variables</i>					
Average population	8,439	8,149.882	16,720.250	0.519	156,222
No conflict	8,439	0.748	0.434	0	1
Average nighttime lights	8,439	6.748	6.300	2.846	60.540
Average travel time	8,439	151.513	198.384	12.842	6,679.209
<i>Panel F: Weather Variables</i>					
Average precipitation	8,439	92.383	46.151	0.032	289.335
Average temperature	8,439	24.254	3.723	9.801	30.958
Average drought (SPEI)	8,439	-0.159	0.191	-1.026	0.687

Notes: This table shows the descriptive analysis for the baseline sample (25km buffer). Travel time is in minutes. Normal counts refers to total number of prior projects of each outcome type (HS, MS, and LS) implemented within 25km before the focal project. Unique counts is the number of distinct prior projects of each outcome type within the 25km buffer, counting repeated or overlapping operations only once.

Table A.2: Unique Counts Estimates

	(1)	(2)	(3)	(4)	(5)	(6)
	Dependent Variable: Current HS projects					
No. Prior HS projects	-0.0362** (0.0159)	-0.0575*** (0.0169)	-0.0599*** (0.0169)	-0.0581*** (0.0173)	-0.0581*** (0.0173)	-0.0615*** (0.0171)
No. Prior MS projects		0.0429*** (0.0161)	0.0394** (0.0161)	0.0406** (0.0164)	0.0402** (0.0166)	0.0385** (0.0164)
No. Prior LS projects			0.0485** (0.0236)	0.0501** (0.0238)	0.0499** (0.0238)	0.0503** (0.0237)
Number of projects	632	632	632	632	632	632
Observations	8,439	8,439	8,439	8,439	8,439	8,439
Within adjusted R ²	0.00507	0.01203	0.01312	0.01304	0.01292	0.01966
Dependent variable mean	0.44259	0.44259	0.44259	0.44259	0.44259	0.44259
ADM ₂ FE	Yes	Yes	Yes	Yes	Yes	Yes
Evaluation year FE	Yes	Yes	Yes	Yes	Yes	Yes
TTL FE	Yes	Yes	Yes	Yes	Yes	Yes
Sector FE	Yes	Yes	Yes	Yes	Yes	Yes

Notes: The table reports coefficients from fixed effects regressions of project success (a binary indicator equal to 1 if the project is rated Highly Satisfactory) on measures of prior local project experience within a 25km buffer. Columns (1) to (6) use unique counts of prior projects rated HS, MS, or LS, respectively. All models include ADM₂, evaluation year, TTL and sector FE and control for average local population density, conflict incidence, nighttime lights, travel time, precipitation, temperature, and drought during the duration of project. Standard errors are clustered by project ID. *Significance codes:* ***: 0.01, **: 0.05, *: 0.1.

Table A.3: Robustness to Excluding Projects Without TTL Information

	(1)	(2)	(3)	(4)	(5)	(6)
	Dependent Variable: Current HS projects					
	TTL Q. controlled	TTL Q. interacted	TTL Exp. controlled	TTL Exp. interacted	TTL Q. and Exp. controlled	TTL Q. and Exp. interacted
Prior HS projects	-0.0160*** (0.0059)	-0.0122* (0.0064)	-0.0210 (0.0159)	-0.0306 (0.0240)	-0.0164*** (0.0060)	-0.0173*** (0.0059)
Prior MS projects	0.0029 (0.0074)	0.0027 (0.0074)	0.0051 (0.0102)	0.0054 (0.0103)	0.0037 (0.0076)	0.0039 (0.0075)
Prior LS projects	0.0271 (0.0167)	0.0270 (0.0168)	0.0541 (0.0400)	0.0538 (0.0402)	0.0268 (0.0169)	0.0265 (0.0164)
TTL quality	0.9795*** (0.0252)	0.9820*** (0.0252)			0.9796*** (0.0254)	1.024*** (0.0282)
Prior HS projects × TTL quality		-0.0088 (0.0073)				
TTL experience			0.0002 (0.0008)	0.0002 (0.0008)	0.0003 (0.0005)	0.0006 (0.0006)
Prior HS projects × TTL experience				0.0002 (0.0004)		
TTL (quality × experience)						-0.0011** (0.0005)
Observations	4,518	4,518	4,518	4,518	4,518	4,518
Within adjusted R ²	0.76910	0.76921	0.00690	0.00690	0.76958	0.77160
Baseline controls	Yes	Yes	Yes	Yes	Yes	Yes
ADM ₂ FE	Yes	Yes	Yes	Yes	Yes	Yes
Evaluation year FE	Yes	Yes	Yes	Yes	Yes	Yes
TTL FE	No	No	No	No	No	No
Sector FE	Yes	Yes	Yes	Yes	Yes	Yes

Notes: This table assesses the robustness of Table 4 results by excluding projects that lack complete information on team leaders. The dependent variable is a binary indicator equal to 1 for projects rated HS. All models include ADM₂, evaluation year and sector FE and control for average local population density, conflict incidence, nighttime lights, travel time, precipitation, temperature, and drought during the duration of project. Standard errors are clustered by project ID. *Significance codes:* ***: 0.01, **: 0.05, *: 0.1.

Table A.4: Logit Regression

	(1)	(2)	(3)
	Dependent Variable: Current HS projects		
	Indicator	Normal Counts	Unique Counts
Prior HS projects	-1.271*** (0.4594)	-0.2482** (0.1145)	-0.6652*** (0.2082)
Prior MS projects	0.5686 (0.3984)	0.0921 (0.0811)	0.3551 (0.2201)
Prior LS projects	0.6475 (0.5036)	0.4429 (0.2713)	0.6359 (0.4156)
Number of projects	339	339	339
Observations	3,165	3,165	3,165
Within adjusted R ²	0.02583	0.02195	0.02891
Dependent variable mean	0.49100	0.49100	0.49100
Baseline controls	Yes	Yes	Yes
ADM ₂ FE	Yes	Yes	Yes
Evaluation year FE	Yes	Yes	Yes
TTL FE	Yes	Yes	Yes
Sector FE	Yes	Yes	Yes

Notes: The table shows estimating the baseline results with a logit model. All regressions include multiple FE (region, year, TTL, and sector) and the full set of baseline controls. Clustered standard errors (by project ID) are reported in parentheses. *Significance codes:* ***: 0.01, **: 0.05, *: 0.1.

Table A.5: Robustness to Alternative Clustering Levels

	(1) cluster = project	(2) cluster = ADM ₂	(3) cluster = two-way
No. Prior HS projects	-0.0193** (0.0075)	-0.0193*** (0.0056)	-0.0193*** (0.0071)
No. Prior MS projects	0.0121** (0.0056)	0.0121*** (0.0024)	0.0121*** (0.0041)
No. Prior LS projects	0.0205 (0.0135)	0.0205* (0.0116)	0.0205 (0.0132)
Observations	8,439	8,439	8,439
Within adjusted R ²	0.01524	0.01524	0.01524
Standard errors	Project level	ADM ₂	Project level & ADM ₂
Baseline controls	Yes	Yes	Yes
ADM ₂ FE	Yes	Yes	Yes
Evaluation year FE	Yes	Yes	Yes
TTL FE	Yes	Yes	Yes
Sector FE	Yes	Yes	Yes

Notes: This table reports robustness of the baseline estimates to alternative clustering levels for standard errors. The dependent variable is current HS rating. The key independent variable is the number of prior HS-rated projects within a 25km buffer before project start. Each column differs only in the level at which standard errors are clustered: Column (1): clustered by project ID (baseline); Column (2): clustered by region (ADM₂); Column (3): two-way clustering by project and region. All regressions include multiple FE (region, year, TTL and sector) and the full set of baseline controls. *Significance codes:* ***: 0.01, **: 0.05, *: 0.1.

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