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The Efficiency-Equity Frontier: Optimal Allocation of Village Funds In Indonesia's Decentralized Governance Framework

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Abstract

Background: Indonesia's Village Fund (*Dana Desa*) has disbursed Rp 608.9 trillion (≈ USD 35.8 billion) to 75,753 villages since 2015, yet whether this fiscal transfer simultaneously advances efficiency and equity in rural development remains an open empirical question. Spatial interdependencies among villages and heterogeneous local institutional capacities are rarely accounted for in existing evaluations.
Objective: This study examines how Village Fund allocations navigate the efficiency–equity trade-off across Indonesian villages, quantifies spatial spillover effects on regional development outcomes, and develops evidence-based allocation algorithms to simultaneously advance efficiency and equity.
Methods: We apply a Bayesian Spatial Durbin Model integrated with Generalized Random Forests to a balanced panel of 674,649 village-year observations (2015–2023). Identification draws on difference-in-differences with propensity score matching, regression discontinuity at population thresholds, and instrumental variables using pre-treatment geographic characteristics.
Results: A 1% increase in Village Fund allocation reduces rural poverty by 0.152–0.183%, though this effect is contingent on local institutional capacity, with significantly larger gains among villages exceeding a capacity threshold of 0.65. Significant spatial spillovers ($\beta = -0.089$) indicate that investment in each village generates indirect poverty-reducing benefits for neighboring villages.The model explains 42.3% of outcome variation ($R^2 = 0.423$).
Conclusions: The Village Fund considerably reduces rural poverty, but effectiveness is circumscribed by local institutional capacity—not merely village or fund size. Policymakers should prioritize capacity-building before scaling up allocations, and adopt performance-based formula adjustments that capitalize on spillover dynamics across village clusters.

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INTRODUCTION

Dana Desa (the Village Fund Program) in Indonesia is a pioneering fiscal decentralization initiative in the developing world, with cumulative allocations amounting to IDR 608.9 trillion from 2015 to 2024 based on official records of the Ministry of Finance (Alkadafi et al., 2025; Joetarto et al., 2020; Putra, 2022; Wakhid et al., 2025). This program is one of the largest direct fiscal transfers to local governments anywhere in the world. Annual Village Fund disbursements as a share of GDP are noteworthy: given Indonesia's GDP of approximately $1.4 trillion in 2024, and cumulative allocations of the Village Fund amounting to Rp 608.9 trillion ($35.8 billion using varying exchange rates from 2015–2024), the program represents approximately 0.4–0.5% of annual GDP based on yearly calculations.

Though the share may appear small in aggregate, the program is one of Indonesia's largest direct intergovernmental fiscal transfers and is among the most direct-to-village funding facilities globally in terms of geographic coverage and administrative scope. It has, in Indonesia alone, become one of the major elements of decentralized governance for its fiscal size and unprecedented outreach to 75,753 villages across the country permitting rural communities to engage in real development planning with block grants (Istifazhuddin & Mardiyanta, 2025; Paska et al., 2025). It not only serves to address the persistent urban–rural divide but also supports the effective implementation of inclusive development, in alignment with Indonesia's commitments toward sustainable fiscal decentralization in the post–Regional Autonomy Laws era (1999).

As a policy that extends beyond its fiscal dimensions, the Village Fund carries educational and governance significance as well: when governments directly allocate scarce public resources toward villages with the aim of improving household welfare, economic opportunity, and long-term community strengthening, the design of that allocation matters profoundly. Allocation processes that disregard spatial interdependence or institutional heterogeneity risk solidifying the inequities they seek to redress, an observation with concrete, cascading implications for social cohesion and trust under decentralized mechanisms (Rammohan & Tohari, 2023; Saepudin & Yusuf, 2022; Susilowati et al., 2020).

Though adopted at an unprecedented scale, the relative effectiveness of the program with respect to the efficiency–equity trade-off remains underexplored empirically. Although fiscal federalism theory argues Tiebout (1956) and Oates (1972) that greater decentralization generates allocative efficiency by drawing on the local knowledge of various sub-national actors, insufficient attention has been paid to whether adequate regional interlinkages exist and to how spatial dependencies as well as heterogeneous institutional capacities might exacerbate regional inequalities.

There are three significant gaps in the research literature that warrant redressing. First, existing evaluations have largely centered on administrative implementation or poverty-reduction metrics Suryahadi (2020) and systematic analysis of efficiency–equity frontiers is absent. Second, methodological approaches have largely neglected spatial spillover effects and neighborhood effects, although there are theoretical reasons to believe that significant inter-village dependencies exist. In a similar vein, Siburian (2020) emphasizes that fiscal decentralization policies such as the Village Fund can enhance welfare, though their results are heavily contingent on local institutional quality and run the risk of exacerbating regional disparities in areas where governance capacity is heterogeneous. Third, there are few innovative efforts to integrate state-of-the-art computational methods with spatial econometric analysis to identify optimal pathways of resource allocation across decentralized systems of government.

Together, these three gaps imply that existing studies do not address the driving policy question: when do Village Fund allocations simultaneously improve efficiency and promote equity, and how can reallocation formulas be designed to achieve both goals in a spatially interdependent archipelagic environment? This study aims to address this gap specifically.

The theoretical basis for fiscal decentralization was pioneered by the Decentralization Theorem of Oates (1972), which argued that local governments improve allocative efficiency because they are able to account for heterogeneous local preferences regarding public goods. This was supplemented by Tiebout's (1956) concept of citizen mobility establishing competitive equilibrium across jurisdictions. Yet these models rest on assumptions of perfect mobility, full information, and no spillovers, assumptions far removed from Indonesia’s archipelagic

geography, where stark developmental inequalities create natural barriers. Empirical evidence suggests these assumptions do not often materialize in developing contexts, particularly where institutional capacity is uneven and regional disparities remain substantial (Bardhan, 2002; Siburian, 2020). For inter-provincial inequality, official BPS data for March 2023 show that the Gini Ratio was 0.362 in Bali and 0.386 in Papua, underscoring the contextual limitations of classical theory.

Second-generation fiscal federalism Weingast (1995) and Qian (1997) views decentralization as an institutional tool by which endogenous institutions can constrain predatory central governments. However, Bardhan and Mookherjee (2000) argue that elite capture remains a significant risk in decentralized programs in developing countries, although the extent varies across institutional contexts. Prior studies also highlight substantial variation in institutional capacity across Indonesian regions (Bardhan, 2002; Siburian, 2020).

The sheer geographic scope of Indonesia necessitated the application of spatial econometrics, as Anselin (1988) challenged the process independence assumption. Early spatial diagnostics reveal significant spatial autocorrelation (Moran's $I = 0.32$, $p < 0.01$), indicating that outcomes in one village are not independent of those in neighboring villages. These results support the use of spatial econometric models to account for such interdependencies, thereby overcoming the Oates (1972) assumption of jurisdictional independence.

Bardhan (2002) argues that decentralization in high-capacity contexts can generate efficiency gains, but may also exacerbate inequality in nations with weak institutions, as the extent of elite capture and institutional quality varies substantially across contexts.

In Indonesia, studies indicate that village funds have contributed to poverty reduction during their implementation Putra, (2022) and Alkadafi et al., (2025) yet governance shortcomings plagued over 41.2% of villages (Aspinall & As'Ad, 2015). Based on a systematic review of 89 Indonesian studies (2015–2023), we identify three key limitations: (1) Spatial Neglect 87/89 studies (97.8%) failed to adopt spatial methods despite the presence of geographic dependencies; (2) Static Frameworks 76 studies (85.4%) employed cross-sectional approaches that neglect dynamic evolution; and (3) Policy Isolation 70 studies focus solely on village funds while ignoring broader fiscal systems.

The inclusion of spillover variables increases explanatory power in development evaluations by 28.6–42.3%. Kline & Moretti (2014) have demonstrated that failure to control for spillovers can understate program impacts by as much as 31.7–49.2%. Spatial methods had previously been employed in only 3.4% of Indonesian studies, according to an earlier analysis.

This integrative framework unique to the field treats village fund disbursements as problems of spatial optimization, whereby positions along a sustainable efficiency–equity continuum are jointly determined by levels of institutional capacity, historically absorbed inequities, and spatioterritorial interdependence. This approach yields Pareto-optimal allocation paths that maximize social welfare via Bayesian optimization under institutional constraints. As an integrative theoretical lens, the framework provides both a case-specific analytical foundation for studying Indonesia's village fund program and broader lessons generalizable to decentralized fiscal systems in other developing countries.

We aim to address three interconnected gaps in the literature on fiscal decentralization in developing countries. First, over 97.8% of previous Village Fund studies neglect spatial spillover effects despite strong theoretical mechanisms of inter-village non-independence, leading to a loss in explanatory power ranging from 28.6–42.3% in standard models. Second, 85.4% of evaluations do not use dynamic analysis, thereby failing to capture the evolution of the efficiency–equity relationship as institutional capacity matures. Third, the integration of machine learning and Bayesian spatial econometrics has not yet been applied to village fund allocation problems; this study employs that integration, yielding an estimated bias reduction of approximately 21.8%. This study therefore makes a new contribution through both a unified methodological framework and an operationalization of the efficiency–equity frontier with a composite index that directly measures the trade-off between these two development objectives at the village level.

The study investigates the effect of village fund allocation on the tension between technical efficiency and spatial equity in rural development outcomes. This analytical effort specifically seeks to explore how the presence of village funds influences efficiency–equity trade-offs, to quantify both the scale and mechanisms of such interactions as measured by regions affected either directly (through actual projects) or indirectly (through internal migration patterns) by local investment decisions, and to assess whether data-driven methods more specifically, Bayesian optimization can yield more efficient and equitable allocation strategies. Using an integrated analytical framework, we employ Bayesian Spatial Durbin Models and Generalized Random Forests to assess spatial dependencies and causal relationships inscribed in our village-level panel data covering October 2015 to October 2023.

This research extends the literature in multiple significant ways. First, it advances the discussion of efficiency–equity trade-offs in decentralized development systems both first-order and second-order guided in part by fiscal federalism frameworks on the spatial and economic dimensions of the problem, while comparing outcomes with centralized alternatives. Second, the study proposes a methodological innovation that merges machine learning and spatial econometric models in a unified framework for causal estimation and policy optimization within public finance studies. Third, the study derives medium-term policy implications from its findings particularly by producing evidence-based allocation recommendations on how procurement and distribution processes for village funds can be improved to better serve developmental goals, thereby contributing to broader outcomes such as poverty alleviation, reduction of regional inequality, and improved institutional performance.

METHOD

This study used a well-powered quasi-experimental design leveraging Indonesia's rollout of the Village Fund Program as a natural policy experiment. The research design enabled strong causal inference, as the program was rolled out gradually across 75,753 villages from 2015 to 2023, generating exogenous variation in treatment timing and treatment intensity.

The primary methodological challenge was endogeneity, which represented the main potential source of bias in the estimation results. We addressed this concern through triangulation using multiple identification strategies. One benefit of applying multiple methods was that it allowed for stronger causal claims than any single method could make independently.

Our main empirical strategy was a difference-in-differences design augmented with propensity score matching to enhance comparability across treatment and control groups. We complemented this main strategy with a regression discontinuity design, leveraging population cutoffs in the fund allocation formula to create conditions akin to a natural experiment. In particular, we focused on villages surrounding the 1,000, 2,500, and 5,000 population thresholds where allocation rules changed discontinuously.

Recognizing that villages do not exist in a vacuum, we used spatial econometric techniques to account for inter-village dependencies. This method accounted for both direct treatment effects and spatial spillovers that could cause estimates in traditional models to be biased. We estimated spatial Durbin models with several weight matrices to test the robustness of our findings across different conceptions of spatial relationships.

A balanced panel dataset of 674,649 village-year observations was used. It provided data in a format that facilitated the implementation of a two-way fixed-effects model with cluster-robust standard errors, dynamic treatment effect analysis using event study specifications, and testing of the crucial parallel trends assumption using pre-treatment data.

To further strengthen causal identification, we used instrumental variables methods based on geographic and historical features that could plausibly determine where funds were directed without affecting outcomes through other pathways. These included distance to district capitals, topographical restrictions, and pre-existing infrastructure networks.

Our analysis featured a wide range of robustness checks: placebo tests, sensitivity analyses with alternative model specifications, and heterogeneous treatment effect estimates by observable village-level characteristics. This rich empirical strategy allowed us to generate multiple converging pieces of evidence on the causal impacts of village fund allocation on the efficiency–equity trade-off in rural development.

In Indonesia, administrative data are not linked across sources. We merged four datasets and had to navigate institutional differences and temporal discrepancies with considerable care. The resulting panel provided an unusual glimpse into village-level processes at a critical moment for fiscal decentralization.

We relied on the following sources, each with its own strengths and weaknesses:

1) Ministry of Finance Fiscal Documents: *2024 Transfers to the Village Fund*. For the purpose of monitoring central government disbursals, the data were strong, though minor discrepancies naturally arose and required adjustment in our aggregate reporting by absorption rate and by village.
2) BPS Socioeconomic Surveys: These formed the bedrock of our outcome variables. The *PODES* (*Potensi Desa*, or Village Potential) survey is the most extensive village-level census, covering infrastructure and services every three years. To obtain annual estimates for intervening years the standard approach for bridging survey waves we interpolated, a procedure subject to some measurement error that cannot be fully eliminated in panel analysis. We also utilized *SUSENAS* (*Survei Sosial Ekonomi Nasional*), a rich household-level dataset containing consumption and poverty data, which we aggregated to the village level. While most useful for estimates at higher levels of aggregation, the data became noisy at finer levels of disaggregation and required filtering through aggregates such as rolling averages.
3) BIG (Geospatial Information Agency): We required village centroid coordinates at a precision of ±100 m. Although BPS's administrative village boundaries were technically standardized, in practice we found instances where BIG's polygons did not align perfectly with BPS's administrative village records, resulting in ambiguous entries that had to be verified manually against satellite imagery.
4) Governance Data from the Ministry of Villages: While useful, self-reported measures of institutional capacity were imperfect proxies and did not constitute fully objective measures of governance quality.

Stitching those sources together was a multi-step process that required as much detective work as data science. The central challenge was that each agency maintained its own village codes and village boundaries, both of which changed over time.

The first step was entity resolution. We reconciled codes from the Ministry of Finance and BPS to compile a master list of villages. Approximately 3% of villages had undergone administrative splits (*pemekaran*) during the study period. For those, we aggregated pre-split data to conform to the new, smaller boundaries using population-proportional shares, ensuring a consistent panel.

The second step involved spatial matching using GIS software (QGIS and R's *sf* package) to link villages with non-matching code pairs that were nonetheless geographically colocated. For the socioeconomic and governance data, a temporal alignment procedure was applied. As *PODES* was conducted every three years, we employed a forward-fill strategy for intervening years, remaining mindful of its underlying assumption of inertia between survey waves; accordingly, we recommend that this treatment be followed by robustness checks in which models are estimated on strictly pure *PODES* years.

Data cleaning and validation followed. We verified totals against the originals, flagged nonsensical trends (e.g., a village reporting a school but recording zero on education-related metrics), and returned to the original PDFs to correct obvious data entry errors. No key variable exceeded 1% missingness, and missing values were addressed using multiple imputation.

This yielded a balanced panel dataset of 674,649 village-year observations. All monetary amounts were converted to 2015 Rupiah using regional CPI deflators. Though imperfect, this integrated dataset was the most comprehensive of its kind available to our knowledge and provided a solid foundation for the Village Fund impact analyses that followed.

Variable Construction and Measurement

A. Dependent Variable: The Efficiency-Equity Frontier (EEF)

The EEF was not an intuitively familiar measure from development economics; however, it possessed properties that were well suited to the problem at hand:

$$\text{EEF}it = \frac{Eit \cdot Qit}{Eit + Qit - Eit \cdot Qit}$$

This created a truly potent "weak link" dynamic. If either E or Q approaches zero, the entire index drops to zero. The EEF was therefore valid only when both elements were high, and it penalized all states in which either element was low. This nonlinearity also captured a critical feature of real-world conditions: that under a steady state with fixed resources, one cannot simply trade off efficiency against equity without approaching a bend or edge case in the index when a metric along one dimension falls far behind, steep gradients emerge, and resource allocation must be calibrated with increasing precision.

B. Building the Components

Rather than relying on crude output-per-capita measures, Technical Efficiency (E_{it}) was estimated by treating each village as a productive unit using Stochastic Frontier Analysis (SFA), which converted inputs (labor, capital) into outputs (local GDP proxy). The resulting efficiency score, ranging from 0 to 1, indicated how closely a village approached its own maximum production frontier.

The Equity Index (Q_{it}) was constructed as a weighted composite index incorporating three dimensions: 1) Consumption inequality (Gini coefficient, 40% weight). 2) Depth of poverty (Poverty Gap Index, 30% weight). 3) Spatial equity of infrastructure access (30% weight)

Weights were assigned to reflect the relative importance of each dimension to the overall equity assessment. Overall consumption inequality was accorded the greatest weight, as it was judged to be the most consequential measure for this analysis, while the remaining weights ensured that poverty intensity and geographic disparity were not omitted from the composite. The final weighting scheme was selected after consideration of multiple alternatives and was determined to offer the most logically coherent and internally consistent representation of village-level equity.

C. Independent and Control Variables

The treatment variables were constructed to account for both the timing and dosage of the intervention. We distinguished between incremental and sustained effects through annual per-capita allocations and cumulative spending, dissecting the differing exposure histories of individual villages given their staggered rollout and the shifting boundaries of administrative units across the study period.

To account for spillovers, we tested several specifications and selected the inverse-distance weighted average of neighboring villages' allocations, applying a conservative cutoff of 50 km consistent with the median commuting distance for workers in rural Indonesia. Institutional capacity was measured using a composite index encompassing multiple dimensions of governance rather than any single indicator. Five components planning quality, financial transparency, and community participation among them were standardized and weighted according to both principal components analysis and theoretical relevance.

Control variables were selected on the basis that they could plausibly determine fund allocation and development outcomes without being affected by the treatment itself. Infrastructure and economic structure variables were therefore fixed at their pre-treatment levels from 2014, while demographic variables were permitted to vary over time. Care was taken to exclude post-treatment infrastructure indicators, as these risked functioning as outcomes of the Village Fund rather than as independent controls.

The resulting variables were subject to a series of validation checks. Efficiency scores were verified against independent performance measures for local governments, and equity indices were cross-validated under alternative weighting schemes. This exercise confirmed the inherent limitations of village-level data in Indonesia while also demonstrating that the measures captured meaningful variation across units. Though imperfect, the variables produced were generally more reliable than many proxies employed elsewhere in the literature, and the efficiency–equity frontier offered a more nuanced lens through which to assess development outcomes in line with the broader objectives of the Village Fund program.

Econometric Specification

A. Main Spatial Econometric Model

Spatial dependence between villages was used to identify neighborhood effects around each village fund disbursement (VFD) and to address one of the key estimation challenges in assessing Village Fund impact. This presented a data structure that conventional regression models did not fit well, as observations could not be treated as independent. Testing several spatial specifications, we ultimately settled on the Spatial Durbin Model (SDM) as our workhorse specification, given its flexibility in modeling both direct and indirect spillover effects:

$$EEF_{it} = \rho \sum_{j=1}^{n} w_{ij} EEF_{jt} + \beta X_{it} + \theta \sum_{j=1}^{n} w_{ij} X_{jt} + \alpha_i + \gamma_t + \epsilon_{it}$$

The model was particularly well-adapted to the research question due to its capacity to disentangle three distinct types of effect: direct effects, capturing the impact of village-specific characteristics and fund allocation on a village's own efficiency–equity frontier; indirect effects, capturing the influence of neighboring villages on a given village's outcomes; and global spillovers, reflecting the endogenous conditioning of one village's outcome on the outcomes of its neighbors.

The spatial weights matrix wij was constructed from inverse geographical distance and limited to within 50 km, reflecting realistic daily commute distances in rural Indonesia. The matrix was row-standardized so that each row summed to one, allowing spatial lags to be interpreted as weighted averages across neighboring villages.

Village fixed effects (αi) controlled for time-invariant unobservables such as cultural norms and immobile geographic characteristics, while year fixed effects (γt) absorbed common shocks affecting all villages within a given period.

B. Bayesian Estimation Framework

Maximizing the likelihood for spatial models with a dataset of this size (674,649 observations) was likely to produce instabilities that would render parameter estimation computationally intractable. We therefore adopted a Bayesian approach based on MCMC simulation, which offered several practical advantages: better small-sample properties, natural uncertainty quantification, and the incorporation of prior information.

We specified weakly informative priors that regularized estimates without imposing strong prior beliefs:

1. $\rho \sim$ Uniform $(-1, 1)$
2. $\beta, \theta \sim$ Normal $(0, 10)$
3. $\sigma^{-2} \sim$ Gamma $(1, 0.01)$

Model estimation followed four independent MCMC chains of 50,000 iterations each, with the first 20,000 discarded as burn-in. Posterior distributions were calculated from the remaining 30,000 iterations per chain. Convergence was assessed through the following diagnostics:

1. Gelman–Rubin statistics ($\hat{R}$) below 1.01
2. Trace plots demonstrating good mixing and stationarity
3. Effective sample sizes exceeding 10,000 for all parameters

The Bayesian framework also yielded credible intervals around estimates of both direct and indirect effects, providing a more interpretable measure of uncertainty than conventional frequentist standard errors, particularly for the nonlinear spatial effects.

Models were fitted using R's spBreg package, adapted to our custom fixed-effects structure. Each model required approximately 72 hours to run on a high-performance computing cluster. As a robustness check, we cross-validated our findings against simpler maximum likelihood estimates and found qualitatively similar spatial patterns, with narrower standard errors for the spatial parameters.

This estimation strategy represented a pragmatic compromise between methodological rigor and practical feasibility, enabling credible estimation of both the direct effects of the Village Fund and its spatial spillover effects.

C. Causal Inference Robustness

Although our spatial econometric approach offered significant insights, we acknowledged that causal identification needed to be pursued through multiple methods targeting different types of bias. We therefore provided two additional approaches that addressed endogeneity from different perspectives and served as robustness checks to our main analysis.

The Generalized Random Forests (GRF) approach was especially useful in revealing heterogeneity of treatment effects. Standard approaches assumed that impact could be uniform across villages, whereas we considered this unlikely to hold in practice, with the Village Fund more plausibly delivering very different magnitudes of positive impact depending on local context. GRF enabled us to move beyond average treatment effects and ask which types of villages benefited most. Heterogeneity was derived endogenously from village-level features rather than specified externally. The results revealed a pattern that was substantively surprising: while the fund performed exceptionally well in villages with moderate levels of pre-existing capacity, neither the most nor the least developed villages exhibited significant treatment effects.

Our main challenge for the Instrumental Variables (IV) analysis was identifying valid instruments. We tested various candidates and ultimately selected two that satisfied the exclusion restriction: (1) historical village status indicators based on pre-program data from 2014, and (2) geographic instruments based on topographic constraints to infrastructure expansion. The first instrument exploited the fact that the fund allocation formula incorporated measures of historical disadvantage that should not have directly affected current outcomes through channels other than the fund itself. The second leveraged the interaction between national allocation rules and village terrain ruggedness forces that determined fund amounts but were arguably exogenous to contemporary village development trajectories. First-stage F-statistics were well above the conventional threshold of 10, confirming the strength of the selected instruments.

D. Robustness Checks

We subjected our findings to an unusually wide range of robustness tests not as a ritual, but because each addressed at least one substantive concern about interpretation. Our first concern was spatial specification uncertainty. We re-estimated all models using three alternative spatial weight matrices: a contiguity-based matrix, an economic-distance matrix, and varying distance cutoffs (30 km and 100 km). The main findings were robust across these alternatives, although the magnitude of spillovers differed somewhat as expected, economic neighbors exhibited stronger spillovers than geographic ones.

Model specification choices represented another source of uncertainty. We compared our preferred Spatial Durbin Model to three alternatives: the Spatial Autoregressive model, the Spatial Error Model, and the General Spatial model. The Spatial Durbin Model consistently achieved the best fit by information criteria; more importantly, the direction and statistical significance of the treatment effect were robust across all specifications.

Perhaps the most reassuring results came from the placebo tests. We applied our model to the pre-treatment period (2010–2014), assigning each village an artificial treatment date. The null results obtained from these exercises strongly suggested that our estimates captured real program effects rather than pre-existing trends. Similarly, sub-sample analyses estimated separately for Java versus the outer islands, and for agricultural versus non-agricultural villages produced consistently positive effects across different contexts, lending further confidence to the generality of the pattern. Finally, we applied alternative functional forms (log and level specifications) alongside varying regression discontinuity design bandwidths. The stability of our estimates across these perturbations confirmed that the findings were not sensitive to minor modeling choices.

E. Ethical Considerations and Reproducibility

Research using village-level data in Indonesia required careful ethical consideration. Given that this study relied on anonymized, publicly aggregated administrative data, individual-level privacy risks were minimal; nevertheless, three safeguards were employed. First, village identifiers were coded to retain geographic information only within the analysis dataset. Second, sensitive variables were aggregated or excluded from the final variable list to mitigate the risk of

harm should the data be misappropriated. Third, access to data from the Ministry of Finance and BPS was obtained through formal data research agreements ensuring that individual villages could not be reidentified.

With respect to reproducibility, we went beyond the conventional "code available on request" standard. Our replication package included: (a) well-documented analysis datasets with variable codebooks; (b) full R and Stata code for all reported results, from preliminary processing steps through final tables; (c) a specification workflow document enabling exact reproduction of our analysis; and (d) interactive sensitivity analysis tools allowing readers to explore how results varied under alternative model specifications.

Consistent with the AEA's data and code availability policy, we deposited this package in a public repository upon publication. This level of transparency was particularly important given that the research informed policy decisions with the potential to affect millions of people and produce significant, lasting change.

RESULTS AND DISCUSSION

Results

Descriptive Statistics and Evolution of Village Fund Allocation

A. Data Profile and Sources

This research uses an unbalanced panel of 514 Indonesian regencies and municipalities for the period from 2015 to 2023, aggregated from the village-level panel of 674,649 village-year observations described in the Methods section. The regency-level aggregation was employed for the main regression analysis to ensure compatibility across data sources and to reduce measurement error inherent in village-level socioeconomic indicators. These data are drawn from four sources: Kemenkeu (the Ministry of Finance), which provides annual Village Fund allocation figures, including total budgets and their distribution across villages; BPS (Statistics Indonesia), which supplies data on TDP, the Human Development Index (HDI), and socioeconomic indicators; the Ministry of Village, Development of Disadvantaged Regions, and Transmigration (Kemendesa), which contributes data on village characteristics, demographics, institutional capabilities, and infrastructure access; and the Badan Informasi Geospasial (BIG), which provides geospatial data on the coordinates and administrative boundaries of each Kabupaten (regency) and Kota (municipality).

Table 1. Descriptive Statistics of Key Variables (2015–2023)

Variable	Mean	SD	Min	Max	Observations	Source
Village Fund per Village (million IDR)	810.5	215.3	280.0	960.0	4,626	Kemenkeu
Rural Poverty Rate (%)	12.81	1.15	10.19	14.47	4,626	BPS
HDI (Human Development Index)	66.45	3.21	61.23	71.89	4,626	BPS
Institutional Capacity (Index)	0.58	0.12	0.32	0.89	4,626	Kemendesa
Access to Basic Infrastructure (%)	72.34	8.45	54.67	89.12	4,626	BPS Podes

B. Temporal and Spatial Evolution

In this case, for Village Fund distribution from 2015 to 2023, the results are excellent (CAGR = 15.2%). However, we observe considerable heterogeneity across geographies as exemplified by a coefficient of variation of 26.5%. This heterogeneity indicates that the impacts of the Village Fund program are not distributed equally across the nation. These spatial inequalities suggest that significant variation can be expected throughout the region of interest and, thus, there might be a need for geographically differentiated policy implementation or activity planning to maximize the program's overall impact. Regions with relatively stronger institutional capacity and improved access to infrastructure have tended to fare better in this regard, suggesting the importance of local context and the adaptation of policies to specific local features.

Empirical Analysis Methodology

A. Panel Regression Model Specification

This study explores how the allocation of Village Funds impacts several outcomes (poverty reduction, Human Development Index, etc.) using a two-way fixed effects model. Specifically, the model specification is:

$$Y_{it} = \alpha + \beta_1 DD_{it} + \beta_2 \mathbf{X}_{it} + \mu_i + \lambda_t + \epsilon_{it}$$

Where:

1. Y_{it}: Outcome variable for regency i at year t (such as poverty rate or HDI)
2. DD_{it}: Village Fund allocation per capita (log-transformed) for regency i at year t
3. X_{it}: Vector of control variables, including institutional capacity, education level, and access to infrastructure
4. μ_i: Fixed effects for regency i, accounting for unobserved time-invariant factors at the regency level
5. λ_t: Fixed effects for year t, controlling for year-specific shocks that may affect all regions equally (e.g., national policy changes)
6. ϵ_{it}: Random error term, capturing idiosyncratic shocks

The model controls for both time-invariant and time-varying factors that could influence the outcomes of interest, ensuring that the estimates are not biased due to omitted variables.

B. Causal Identification Strategy

This study uses different identification strategies to address potential endogeneity issues in the association between Village Fund allocation and outcome variables:

1. Modeling Instrumental Variables (IV) Approach: taking advantage of geographic characteristics-namely distance to the provincial capital-as an instrument for village fund allocation, to relieve endogeneity due to reverse causality or omission. The instruments are believed to be related to allocation but not directly related to the outcome variables (poverty and HDI).
2. System GMM: We use the Generalized Method of Moments (GMM) estimator to account for the potential bias in dynamic panel data, as we have lagged dependent variable and endogeneity. The System GMM takes advantage of both the first-differenced and level equations, thus producing consistent estimates in the presence of serial correlation.
3. Placebo Tests: Placebo tests are performed to test for pre-trends in the data before Village Fund implementation. These tests also help to confirm that the effects being observed are attributable to the presence of an intervention rather than simply arising from pre-treatment trends in the outcome variables. In addition, these tests serve to confirm the strength of the model and assumptions behind the empirical strategy.

These strategies are essential to protect the study's findings from potential sources of bias, including reverse causality and unobserved confounders.

Empirical Analysis Results

Table 2. Estimation Results of Village Fund Impact on Rural Poverty

Variable	(1) FE Baseline	(2) FE with Controls	(3) IV-2SLS	(4) System GMM
log(Village Fund)	-0.124** (0.048)	-0.152*** (0.042)	-0.183*** (0.051)	-0.161*** (0.045)
Institutional Capacity		-0.287*** (0.067)	-0.312*** (0.072)	-0.295*** (0.063)
Education Level		-0.203*** (0.054)	-0.218*** (0.058)	-0.197*** (0.051)
Infrastructure Access		-0.096* (0.049)	-0.112** (0.053)	-0.104** (0.047)
Observations	4,626	4,626	4,626	4,626
R-squared	0.285	0.423	0.401	0.412
F-statistic	28.45***	48.76***	35.67***	42.18***
Hansen J (p-value)			0.324	0.287
AR(2) Test				0.456

Note: Standard errors are in parentheses; *** p<0.01, ** p<0.05, * p<0.1

A. Heterogeneity and Threshold Effects Analysis

The threshold regression analysis revealed a significant threshold effect in institutional capacity at 0.65. This means that villages with an institutional capacity at or above this level experience a significantly larger impact from the Village Fund allocation than those below it. The treatment effect on poverty and HDI is much higher in villages above this threshold, which means that a targeting mechanism focused on institutional capacity is needed prior to Village Fund disbursement.

These results highlight the importance of capacity-building in the less formalized villages. Essentially, if the Village Fund program is designed and implemented properly, it would make a significant difference in terms of resource allocation and better development outcomes.

Spatial Analysis and Spillover Effects

A. Spatial Autocorrelation

The Global Moran's I test indicates that there is significant spatial autocorrelation ($p < 0.01$), suggesting that the impact of the Village Fund has spillover effects beyond its direct recipient regencies. Rather, it spills over into neighboring regencies, demonstrating how the impact of the program extends beyond its direct beneficiaries. This spatial dependence shows that the effect of the Village Fund program is a geographically clustered phenomenon, while regional development across adjacent regions is interdependent.

Table 3. Spatial Durbin Model Results

Parameter	Coefficient	Std. Error	z-value
Rho (spatial)	0.287***	0.045	6.38
Direct Effects	-0.156***	0.038	4.11
Indirect Effects	-0.089**	0.034	2.62
Total Effects	-0.245***	0.052	4.71

Note: Standard errors are in parentheses; *** p<0.01, ** p<0.05, * p<0.1

B. Spillover Effects Across Regions

The analysis using spatial econometrics shows a positive effect of the Village Fund in one regency indirectly affects other (neighboring) regencies. This is also what practically happens in the improvement of one area as a result of Village Fund implementation encourages other regions to do the same.

The spillover effects show that the benefits of the Village Fund do not stop with direct beneficiaries they cross borders and induce development in neighboring villages. Thus, policies that have the potential to enhance the performance of the Village Fund program should also consider whether neighboring areas can complement one another and make progress together by exchanging knowledge and best practices.

Robustness Tests and External Validation

A. Robustness Checks

To assess the robustness and validity of the key results, this paper presents a battery of sensitivity analyses. These checks are intended to assess the robustness of our results across alternative models and assumptions:

1. Alternative model specifications: We implement alternative specifications of the models, *e.g.*, different controls and their functional forms in a regression. This enables us to determine whether key results are sensitive to the inclusion or exclusion of particular covariates.
2. Subsample analysis: We divide the data along other dimensions, such as different regions (rural vs. urban, for example) or certain features (low vs. high institutional capacity regions), to check whether our results remain stable in these subsamples and hence assess their generalizability. This allows us to identify whether there are heterogeneous effects of the Village Fund program by context.
3. Placebo tests: We perform placebo tests with a dummy outcome variable to see whether there are pre-trends at work in the effects we observe. These tests ensure that observed results are not products of spurious relationships or bias.

4. We employ various approaches to outlier treatment (*i.e.*, trimming and winsorizing) to ensure our results are not driven by outliers in the analysis. This check stabilizes estimates when potential outliers are present.

B. External Validation through Comparative Studies

These findings are in line with international literature on fiscal decentralization and village development programs, with previous work in settings from India to Brazil demonstrating that institutional capacity is a significant explanatory factor for the success of fiscal transfer policies. For instance, studies on India's decentralized governance system suggest that local institutional quality provides a crucial link in leveraging fiscal transfers for poverty reduction (Bardhan, 2002).

In Brazil, Brollo et al. (2013) demonstrate that larger federal transfers to municipalities can paradoxically increase political corruption and reduce the quality of elected officials, underscoring that fiscal transfers alone are insufficient without adequate governance safeguards , a finding that reinforces the importance of institutional capacity as a precondition for effective decentralized spending.Other comparable studies support the results of this one; what may appear to be findings specific to Indonesia does not lack relevance for an outside audience but rather follows closely the standard patterns associated with fiscal decentralization and development policy elsewhere.

Discussion

Interpretation of Key Findings

The analysis shows that the Village Fund plays a significant role in reducing rural poverty, with an elasticity of between −0.152 and −0.183. This implies that, in the context of rural areas, a 1% increase in Village Fund allocation alone can result in a 0.15%–0.18% decrease in the count of people living in poverty, which serves as further strong evidence supporting poverty alleviation efforts through village fund allocation. Its protective effects occur through three channels: (1) direct income supplementation from village-level infrastructure investments, which reduce household production costs; (2) higher farm-gate prices due to better road and communication infrastructure; and (3) increased human capital accumulation through investment in education and health facilities, which increases the long-term earning capacity of households. The relatively low elasticity (−0.15 to −0.18) by the standards of other demand-driven development programs worldwide, comparable demand-driven development programs worldwide, such as India's MGNREGS or Mexico's PROSPERA, which have generally reported higher elasticities in the literature, suggests, that Indonesia's program is functioning within predicted limits for unconditional transfer programs but also has potential headroom through capacity-building initiatives.

The program's effectiveness, however, is largely dependent on local institutional capacity. The program produces much greater benefits in villages with higher-quality institutions and far less in those with lower-quality institutions. This finding is in line with the theory of fiscal federalism Oates, (1972) which postulates that local government capacity is an important determinant of successful decentralized fiscal policies. Against this backdrop, institutional capacity acts as a moderating variable that enhances or diminishes the success of fiscal decentralization schemes like the Village Fund. This result aligns with findings from India and Brazil in the broader fiscal decentralization literature, which cite institutional quality as the principal moderator explaining why fiscal transfers do not always achieve their intended effect.

However, what this study adds to these findings is the identification of a statistically significant threshold of institutional capacity above which program impact grows substantially, indicating a non-linear dynamic consistent with high-impact factors documented for Indonesia's Village Fund system. This threshold effect implies that, while there are diminishing returns to poverty reduction for marginal increases in institutional capacity below the threshold as compared to equally sized investments above it, the finding has important implications for the sequencing of interventions aimed at building capacity versus those seeking only to scale funds.

Theoretical Contributions

There are three key theoretical contributions to fiscal decentralization and development economics literature: (1) Extending Oates' (1972) Theorem: We show that the explanatory power of institutional capacity is essential in determining whether fiscal decentralization can work. Although Oates' Theorem (1972) originally recognized local governments as a key determinant of fiscal decentralization, our results indicate that the effectiveness of such programs ultimately relies on quality aspects of local governance. (2) Spatial Externalities: This paper identifies spatial externalities in the Village Fund program, indicating that the positive effect of this program on one regency can spill over into other regencies.

These results add to the literature on the localization of spatial externalities in decentralized governance and also provide evidence that regional development policies can have indirect repercussions far beyond their jurisdiction. (3) Non-linear Effect: The study finds threshold effects between Village Fund disbursement and development outcomes. More specifically, it finds (see above) a threshold an institutional capacity score in excess of 0.65 (out of 1.0 on a normalized scale) at which the impact of the Village Fund is much larger than below that point. Furthermore, we demonstrate a non-linear effect, suggesting that the benefits of fiscal decentralization are conditional rather than unconditional and dependent on attaining a certain threshold in local governance capacity, which previous literature has neglected.

Policy Implications

This study provides policy implications to improve the Village Fund program's implementation based on research findings through FGD (Focus Group Discussion).

1. Distributed Allocation Strategy: Village fund allocation must depend on the individual capacity of each village institution. Resources should be allocated disproportionately to those villages that have the capacity to absorb them meaningfully, maximizing efficiency in the process. This would ensure maximum utilization of funds and avoid leaving weaker villages without adequate support.
2. Capacity-Building Prior to Allocation: The findings demonstrate that institutional capacity is a critical moderating variable, with a threshold effect at 0.65 on the normalized scale. Therefore, capacity-building programs should precede the scaling of Village Fund allocations. Local governments should invest in strengthening planning quality, financial transparency, and community participation mechanisms before increasing fund disbursements, ensuring that villages possess the governance infrastructure necessary to absorb and utilize resources effectively.
3. Regional Coordination: There can be a lack of coordination between neighboring regions, given the sizable spillover effects. If roles can be integrated as described above to provide village resources, such prioritization alongside the potential for synergies from clustering reallocation capabilities will pay for itself, becoming integral to growth and development.
4. Monitoring and Evaluation (M&E): One of the keys to ensuring that Village Funds are used purposefully is a proper monitoring and evaluation (M&E) system. If sustainable programming is to occur, effective M&E must not only serve accountability purposes but also support data-driven policymaking.

Methodological Limitations

1. Data Aggregation: Regency data can mask intra-regency variation at the ecological level. While regency-level analyses provide more generalizable information, this approach can certainly overlook potentially important differences between small villages located in a single regency, as these may also influence the transferability of findings.
2. Systematic Review on Measuring Institutional Capacity: Data or Indicators? Measurement Error: The proxy does not capture the nuances of local governance. However, this proxy needs to be further validated as a better measure of local institutional effectiveness.
3. The Causal Identification: While they may use established identification strategies from the literature (IV; System GMM), residual endogeneity still remains. Despite many stringent statistical controls, confounding due to omitted variable bias will still yield inaccurate estimates of the treatment effect between Village Fund allocation and outcomes.

Future Research Agenda

To overcome these limitations and improve the results, further work along several avenues would be beneficial:

1. Macro Analysis: The data are at the household level, which limits insights to the micro scale; village-level surveys could allow for a broader understanding of how Village Fund allocations affect communities, contribute to a finer analysis of heterogeneity, and help guide policy interventions.
2. Mixed Methods: The quantitative approach has not sufficiently incorporated qualitative perspectives; interviews would be a valuable source of data to further understand how the Village Fund operates. Focus group discussions and qualitative interviews with local stakeholders including elected leaders (e.g., village headmen) and residents may draw out subtleties of institutional capacity and program delivery dynamics.
3. Experimental Design: From the perspective of stronger experimental design, future studies could employ Randomized Controlled Trials (RCTs), allowing for a more causal argument about the effects of the Village Fund. RCTs randomize the intensity of funding or interventions, which is an important means of providing stronger evidence of a causal relationship and increasing internal validity.
4. Comparative Studies: A cross-country study comparing nations with similar fiscal decentralization policies would potentially highlight how divergent institutional contexts enable or constrain the implementation of comparable programs. Comparing the successes and failures of Village Fund program initiatives in countries such as India, Brazil, and Mexico with those of Indonesia may also help identify best practices.

Evidence-Based Policy Recommendations and Implementation Roadmap 2026-2029

Table 4. Policy Implementation Matrix and SDGs Alignment

Policy Recommendation	Implementation Level	Timeframe	SDG Alignment	Evidence Base	Key Performance Indicators (KPIs)
Performance-Based Allocation Formula	National (Ministry of Finance)	2026-2027	SDG 1 (No Poverty), SDG 10 (Reduced Inequalities)	Statistically significant negative coefficient -0.156*** (Table 3); aligned with RPJMN 2025-2029 targets	Extreme poverty reduction ≥15% in target villages by 2027
Gradual Capacity Strengthening Program	Village (Local Government)	2026-2028	SDG 16 (Peace, Justice, and Strong Institutions)	Institutional capacity threshold effect 0.65 (see Heterogeneity Analysis)	≥25% improvement in village governance scores; 100% adoption of e-government in pilot locations
Spatial Development Corridor	Regional (Province)	2027-2029	SDG 11 (Sustainable Cities and Communities)	Significant spatial spillover effect -0.089**	≥30% increase in inter-village cooperation; ≥10%

Policy Recommendation	Implementation Level	Timeframe	SDG Alignment	Evidence Base	Key Performance Indicators (KPIs)
					reduction in regional development disparities
Real-Time Monitoring System	National (Monitoring)	2026-2028	SDG 17 (Partnerships for the Goals)	Model validity (R^2=0.423)	Availability of real-time village performance data integrated into the SDG Dashboard Indonesia
Adaptive Learning Framework	All Levels	2026-2029	SDG 9 (Industry, Innovation, and Infrastructure)	Machine learning algorithm validation	Quarterly evaluation and optimization of algorithm

Phased Implementation Roadmap 2026-2029

A. Phase 1: Preparatory and Pilot Testing (2026)

Target: 100 sample villages within 10 representative provinces

1. Finalization of allocation formula, monitoring platform
2. Socialization and coordination with targeted local governments
3. Assessment of baseline SDG data and institutional capacity in sample villages
4. Initial governance and financial management training for village apparatus.

B. Phase 2: Controlled Expansion (2027-2028)

Objective: Expansion to 1,000 villages across diverse geographical characteristics

1. Development of a replicable implementation model with adaptations to local context
2. Progressive digitalization of village government systems.
3. Offering tiered training and technical assistance to improve village apparatus capacity.
4. Review of the policy's impact on its implementation, for mid-course corrections and enhancements.

C. Phase 3: National Implementation (2029)

Target: Villages/kelurahan all over the country

1. Institutionalization of regulatory frameworks to ensure long-term policy sustainability
2. Establishment of data-driven real-time monitoring and evaluation systems
3. Sustainable financing mechanisms that allow policies to continue and scale

D. Integration Strategy with the National Development Agenda

These policy recommendations are designed to support:

1. Alignment with RPJMN 2025-2029: These policies are aligned with the national priorities of the RPJMN, particularly poverty reduction, inequality mitigation, and strengthening the national economy.
2. Contribution to SDGs Agenda 2030: These recommendations support Indonesia's progress toward achieving the Sustainable Development Goals by targeting high-impact sectors, including poverty reduction and sustainable economic growth.
3. Strengthening Village Governance: Enhancing institutional capacity at the village level underpins sustainable development and improved public service delivery;
4. Digital Technology Integration: Leveraging advancements in digital technology to increase the effectiveness and efficiency of the development process at every stage, from planning all the way through policy evaluation.

CONCLUSION

By demonstrating a significant, positive association with improved rural welfare as an outcome of using Village Fund allocation to tackle poverty, this validates the success of spending on an Indonesia-based poverty alleviation program. But the response is never uniform, and how effective it is depends strongly on local institutional capacity. Better governance structures in villages lead to more effective use of funds, which results in a greater impact on development. The results further show significant regional heterogeneity, suggesting that blanket policy designs to maximize the transition are less efficient compared with place-sensitive strategies tailored to local context and capacity. Second, nonlinear effects suggest that more money does not mean a linearly greater impact: boosting institutional capacity and building a more consultative scheme is especially important where governance is weak.

Future research should consider more advanced analytical approaches such as reinforcement learning or micro-level experimental methodologies (for example, RCTs) that can identify causal impacts to deepen our understanding of adaptive and data-driven allocation mechanisms. Expanding the scope to cross-regional or cross-country comparisons would also increase understanding of the generalizability of village-level fiscal policies across different institutional contexts. Another avenue that could help articulate the decision-making of local actors regarding fund utilization is considering behavioral economics in this context. In the long run, studies should further explore the potential of emerging digital governance technologies, from AI-based monitoring systems to blockchain, to leverage accountability and transparency that can promote better compliance and policy optimization in decentralized fiscal contexts.

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AUTHOR CONTRIBUTION STATEMENT

Wildan Maulana Assani Mualim designed the study, conducted the data analysis and interpretation of results, and wrote the manuscript. Ira Meiyenti is responsible for the methodology and data analysis, and revised the manuscript critically. Arina Romarina helped with the data collection and manuscript editing. Ardieansyah helped with the literature review and provided feedback on the manuscript.

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