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Combating Poverty through Aid: A Critical Analysis of Alternative Models

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Abstract

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INTRODUCTION

Given that concentrated poverty is deepening around the world, the international development community now has even more reason to address this issue. Development aid has ostensibly served as an important policy instrument for promoting the welfare of marginalized communities in the Global South. The effectiveness of such efforts can be evaluated from varying angles but the first test to pass is its relevance to the lives of the most marginalized. This dissertation evaluates the extent to which aid activity is suited to the needs and priorities of recipients using three lenses: 1) needs assessment at the global level, 2) the design of interventions at the country level, and 3) evaluations at the sub-national level. The first chapter identifies the salient dimensions of poverty from the monetary and capability perspectives, using a cross-country analysis for 188 developing countries. The second chapter introduces a framework for analyzing two community development models in Myanmar as a country case study. The third chapter explores whether community development projects reach the poorest villages. It combines satellite imagery with spatial analysis to evaluate sub-national aid distribution. This study suggests strategies to deploy aid resources in a way to maximize their impact on people living in absolute poverty and data-sparse contexts.

CHAPTER 1. THE DISCREPANCY BETWEEN TWO APPROACHES TO GLOBAL POVERTY: WHAT DOES IT REVEAL?

For decades, development communities have attempted to develop poverty measures that can be used to inform need assessment and aid allocation. Building on these efforts, this paper examines the discrepancies between global poverty measures and brings that analysis to bear on identifying the salient dimensions of poverty in developing countries. It first compares the monetary and capability approaches to poverty and identifies comparable indices from each approach: the

poverty headcount ratio (P_0) and the multidimensional poverty headcount ratio (H). This paper then describes the degree of overlap and discrepancy between P_0 and H for 118 developing countries from 2000 to 2014, synthesizing the Multidimensional Poverty Index (MPI), World Development Indicators, and OECD aid activity data. On average, there is a high correlation between the two poverty measures, but considerable discrepancies surface for some countries. I analyze the position of these countries with respect to the fitted line of the two measures, classifying them into income-poor and capability-poor countries. Countries such as Pakistan and Ethiopia, for example, are experiencing "capability poverty" while Uzbekistan and Zimbabwe are experiencing "income poverty." I examine whether aid composition corresponds to the country's relative income and poverty status, finding that capability-poor countries receive marginally higher social sectoral aid compared with economic sector aid. This study suggests that discrepancies between measures of international poverty can be used to target, monitor, and evaluate global aid distribution.

CHAPTER 2 ALTERNATIVE MODELS OF COMMUNITY-LED DEVELOPMENT: IMPLICATIONS FOR POLICY AND PRACTICE

Reconciling the dual imperatives of legitimate state building and efficient service delivery, Community-led Development (CLD) has been praised as "a new form of engagement" in providing aid to fragile states. However, whether or how the CLD represents a new model of practice remains poorly understood. The absence of an analytical framework for distinguishing alternative CLD approaches to development aid hinders both the design of context-specific interventions and the evaluation of their impacts. This dissertation aims to compare two alternative models of CLDs against a backdrop provided by the framework of community-led development. Using document reviews and stakeholder interviews, this paper analyzes two aid projects in Myanmar: the Korean government-supported *Saemaul Undong* (SMU, New Village Movement), which reflects the perspective of the developmental state, and the World Bank-supported National Community-Driven Development Project (NCDDP), which reflects the perspective of the revised neoliberalism. Next, this study proposes the Agency-Power-Dimension (APD) framework for use in describing donors' general CLD aid policies in conjunction with specific CLD projects in Myanmar. The Agency-Power-Dimension (APD) framework is proposed to describe donors' general CLD aid policies in conjunction with specific CLD projects in Myanmar. This study finds that the intervention strategies of SMU and NCDDP differ regarding the main agency of change, the handling of power, and the objectives of projects. SMU engages with government extension workers as the main change agent, and its accountability comes from the performance of projects that focuses on agricultural production. In contrast, NCDDP works with private facilitators, emphasizing the processes of inclusion in the context of public infrastructure development. Previously, impact evaluations of CLDs set hypotheses based on the logical progression of the projects whose indicators are diffused over broad socio-economic domains. The APD framework identifies the main facets of treatment arms in future experimental studies. Policymakers seeking development opportunities in other fragile states can compare East Asian/Southern and Western/Northern approaches and apply it to varying local conditions.

CHAPTER 3: MAPPING COMMUNITY DEVELOPMENT AID: SPATIAL ANALYSIS IN MYANMAR

Aid policy has the potential to alleviate global poverty by targeting areas of concentrated need. However, few aid-determinant studies have analyzed the characteristics of poverty at the sub-national level, and even those studies were conducted with their units of analysis at a high administrative level such as the state. This study intends to fill this knowledge gap by portraying poverty at the granular level, and promoting the evaluation of aid towards the most marginalized communities. The goal of this study is to explore the extent to which community-led-development (CLD) projects take place in poor villages, using the case of Myanmar. It also analyzes how two CLD models, National Community-Driven Development Project (NCDDP) and *Saemaul Undong* (SMU) target needs differently. To collect outcome variables, I develop web scraping algorithms to create comprehensive and up-to-date locations of CLD participating villages (n=12,282). As for exploratory variables, radiance values from nighttime satellite imagery are extracted to estimate wealth at the community level. In addition, I spatially interpolate the DHS wealth index to make inferences on poverty in aid sites. By geospatially matching aid and wealth related data, I test factors that explain variation in the distribution of CLD and different approaches to community development. The results show mixed evidence of poverty-oriented targeting. First, as each increment of the share of a vulnerable population rises, the likelihood of aid presence in that community declines by 4%. Next, the density of community development projects is higher in areas shining brighter. A one unit increase in the nightlight intensity increases the number of projects by 86 within a two-degree radius of a DHS village cluster. Among villages of similar levels of nightlights and population, however, aid goes to areas with lower assets. Last, NCDDP, which emphasizes inclusion and collaboration, supports poorer villages farther away from conflict events. In contrast, SMU, which considers competition conductive to performance, supports more established areas including villages near conflict zones. Unlike previous studies finding that state-level aid allocations favor the richest, this more fine-grained analysis suggests that a need-based allocation is also in place. The nuances captured in nightlight luminosity are also shown to improve predictions of aid distribution. Synthesizing new sources of data can be used to assess area-based interventions in the context of poverty and conflict where traditional survey is too costly.

CONCLUSION

This study draws attention to alternative forms of evidence-based targeting, design, and evaluation of aid from poverty-oriented perspectives. The first chapter reveals that there are 1.5 times more capability poor countries than income poor ones, and the capability poor countries receive marginally higher social sectoral aid relative to economic sector aid. The second chapter finds that the intervention strategies of the revised neo-liberal (NCDDP) and the developmental state (SMU) model differ in terms of the main *agency* of change, the handling of *power*, and the primary *dimension* of projects. The third chapter highlights that community development aid in Myanmar flows to villages with low assets but also with higher nightlight luminosity and a lower proportion of vulnerable populations. These three chapters also speak to the evolution of an aid landscape with a distinctive way of delivering aid and generating empirical evidence. This study concludes with a call for both research and practice to return to the basics, and to begin by considering client and user needs. Grounding development policy in more contextualized knowledge, the development community can better serve the “bottom billion.”

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For many years, I kept returning to school. Like Peter Pan, I found comfort in being a student forever. Academia has been a space that allows me to daydream. It encouraged me to remain curious about my surroundings and taught me how to raise questions and seek some of the answers. This intellectual journey has been supported by many.

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Putting a period at the end of this dissertation, I wonder if I can still be Peter Pan in the world of make-believe -- school. No, because I already grew up with learning. Yes, because I found a way to stay in academia in a research and teaching capacity. This time, I will be dreaming together with my learning community for the difference we can make.

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INTRODUCTION

In 2015, 736 million people, accounting for 10.7 % of the world's population, still live on less than $1.90 a day. Although extreme poverty fell by more than two-thirds since 1990, poverty is now more concentrated in conflict-prone and resource-based economies (Winthrop, Bulloch, Bhatt, & Woods, 2015). This dollar-a-day poverty provides a snapshot of dire poverty around the world but does not show the whole picture. The persistent disparities in the non-income dimensions of development pose key challenge. Compared with the Millennium Development Goals regarding income poverty, non-income goals saw more mixed results (Kenny & Dykstra, 2013; de Janvry, 2015). Facing this issue, the global community now has more reason to confront poverty directly rather than indirectly. A good starting point for concerted action is to address the most dominant feature of poverty in each developing country, drawing insights from different ways of measuring poverty.

Development aid has ostensibly served as an important policy instrument for promoting the welfare of marginalized citizens in the Global South. During the past half-century, at least 3.5 trillion U.S. dollars have been disbursed as official development assistance from more advanced economies to emerging economies. Given the sheer volume of inter-country public transfer, aid effectiveness has been a subject of controversy. One major debate surrounds the issue of "conscious planning" versus "spontaneous solution" school. According to the former, economic development can be achieved through scientific direction and goal setting in the form of a central plan of action that is implemented on a large scale (Myrdal, 1974; Sachs, 2006). By contrast, the latter sees development as a self-organized order that evolves as individuals use their own localized or tacit knowledge (Hayek, 2014; Easterly, 2016). The question is whether both positions can be incorporated into a more "contextualized design of aid," which increases recipients' participation in the process along with their buy-in for the development results.

The effectiveness of aid can be evaluated from varying angles but the first test to pass is its relevance to the lives of the most marginalized. If aid-giving criteria have little to do with the needs and development context of recipients, then there is little reason for aid to be impactful in eradicating poverty and promoting growth (Berthélemy & Tichit, 2004). However, in a world riddled with poverty, data scarcity hampers policy maker's ability to deliver aid to those most in need and assess the intervention from the perspective of its distributive role. The higher the needs, the less confident and available the data. Nonetheless, there is no reason why the aid industry, one in which human lives are at stake, fails to adopt the technologies applied in other fields, where mere dollars are at stake (Mullainathan, 2016).

This dissertation examines 'alternative models' that link poverty and aid. It explores the extent to which aid activity is suited to the needs and priorities of recipients and, to this end, it applies project cycle lenses and macro, meso, and micro scopes in the following: 1) needs assessment at the global level, 2) the design of interventions at the country level and 3) evaluation at the sub-national levels. Figure 1 illustrates how these three themes are mutually related and methods are complementary to one another. The top left cell represents what is common to all three chapters: poverty and aid. Chapter one (rows) analyzes two different approaches to poverty and need, using a cross-country analysis for 118 developing nations. Chapter two (columns) discusses aid models, zooming into a country case study in Myanmar. Tying aid to poverty spatially, chapter three (cells) evaluates the responsiveness of aid to community-level needs across subregions in Myanmar.

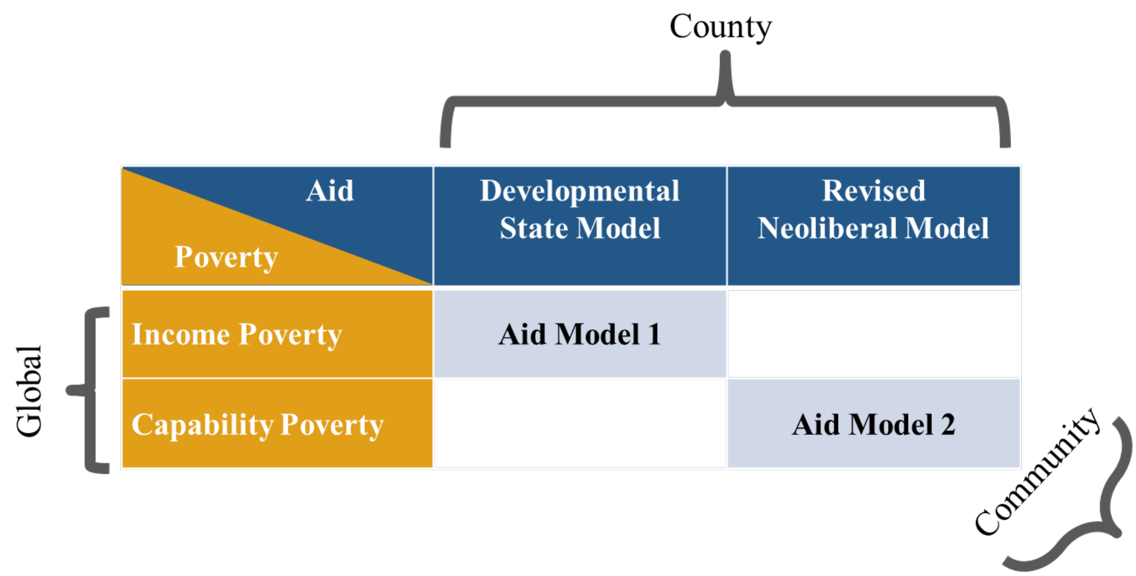

Figure 1. Structure of the Dissertation

The purpose of my dissertation is threefold. First, it identifies the salient dimensions of poverty in developing countries from monetary and capability perspectives. Next, the study discusses how different orientations towards development play out as contrasting aid models in Myanmar. Third, a fundamental but challenging question of whether development projects reach the poorest is addressed using new measurement techniques. This study has real-world implications for global development policy to ameliorate poverty. This study, while engaging in an intellectual discussion of alternative ways of measuring global poverty, implies strategies to deploy aid resources in a way to maximize their impact on people living in absolute poverty. The methodological tools developed in this study are applicable to a broad range of questions in our field as we address poverty and inequality through data-intensive research and practice.

CHAPTER 1. THE DISCREPANCY BETWEEN TWO APPROACHES TO GLOBAL POVERTY: WHAT DOES IT REVEAL?

Introduction

The development community strives to create internationally comparable indices to characterize global poverty. The ways in which poverty is measured not only shapes perceptions of need but also has ramifications for targeting interventions. This community has generated and made available a wide variety of aggregate measures of poverty available. Each one of these poverty indices has been subject to debate, leading to an effort to craft supplementary measures to capture items presumed to be missing items in measures.

The issue may not be the shortage of reasonable measures, but how we take stock of them. It is challenging to devise intuitive but comprehensive measure that satisfy key axiomatic properties rooted in Sen's work (1976). Under the focus axiom, the measure should not vary if the income of the non-poor varies. Under the monotonicity axiom, any income gain for the poor should reduce poverty; and under the transfer axiom, inequality-reducing transfers among the poor should reduce poverty. Given that there is no single best measure of poverty, a more systematic accounting of currently available tools merits attention.

Two dominant approaches to poverty in the international development field are the monetary approach (MA), and the capability approach (CA). In the monetary approach, poverty indicates a lack of the necessary income to meet basic needs; while in the capability approach, it indicates a failure to achieve basic capabilities. While the monetary approach has continued to dominate both development discourse (Summer, 2007) and practice (Jung, 2011), the capability approach has made inroads as a complement to traditional measures.

Studies that juxtapose findings on the basis of monetary and multidimensional measures have often confronted the issue of inconsistency. Growing evidence suggests that poverty estimates based on monetary and multidimensional measures are often loosely associated and that one measure cannot serve as a proxy for the other (Bradshaw and Finch, 2003; Tran et al., 2015). Other studies have compared these contrasting measures yield disparate findings regarding the scope of poverty and how they suggest that poverty may exert differential effects on sub-populations (Roelen, 2017, Alkire and Santos, 2010; Klasen, 2008).

The degree to which there are exceptions and mismatches often leads to debate over whether monetary measures reflect non-monetary outcomes or vice versa. However, such exceptions and mismatches may actually serve as interesting sources of information and have the potential to be used as a policy instrument.

This paper aims to create a taxonomy for characterizing developing countries within monetary and capability poverty indices. It analyzes the position of these countries with respect to the degree of discrepancy between the two poverty indices and categorizes the relevant countries into income poor and capability poor. Following this country classification, I provide a case example of a way in which this taxonomy can be used to understand whether aid target proportionately for income poverty and capability poverty.

Research questions are as follows:

1. What is the degree of discrepancy between the MA and CA poverty indices?
2. How can each developing country be classified by the salient dimension of poverty?
3. To what extent does aid by sector (aid to the economic sector vs aid to the social sector) correspond to a country's relative income and capability poverty status?

Data and Sample

The analysis synthesizes the most up-to-date \$1.90 measures and the largest set of published Multidimensional Poverty Index (MPI) measures for 213 observations of 118 countries from the period of 2000 to 2014. Data in this study are synthesized primarily from three publicly available sources. First, global MPI tables from the Oxford Poverty and Human Development Initiative present an archive of all published MPI estimations. Second, the World Bank's World Development Indicators provide sources for poverty headcount ratio and country characteristics for 135 non-high-income countries from 1990 to 2015. Third, detailed data on Official Development Assistance (ODA) sector allocable aid flows to ODA eligible recipient countries are obtained from the Creditor Reporting System (CRS) code of Organisation for Economic Co-operation and Development (OECD) Development Assistance Committee (DAC). ODA, defined by the OECD DAC, is government aid designed to promote the economic development and welfare of developing countries. Sector-allocable aid is the sum of aid that is designed to assist specific sectors such as education, health, agriculture, civil society and governance, or multisector activities. The sum of aid to the social sector (5-digit CRS code starting with 1), aid to the economic sector (5-digit CRS code starting with 2), and aid to the production sector (5-digit CRS code starting with 3) are calculated for each country by year.

The sample is restricted to countries whose MPI data and poverty headcount data are available. To match the country and year of multidimensional poverty headcount ratio data with the \$1.90 a day income headcount ratio, income poverty headcount variables are filled in by linear interpolation and extrapolation, assuming that the observation on missing poverty is a function of year. For eight data points for five countries (Afghanistan 2010, Egypt 2008, Iraq 2006, Syria 2006/2009, Yemen 2006/2013, Zimbabwe 2006) data on international poverty headcount ratios are not available; thus the national poverty line is used. The missing data imputation increases the number of sample countries from 64 to 123.

Comparison of the Monetary and Capability Measures

MA and CA represent two major perspectives on the definition, measurement, and policy response to poverty in the field of international development aid. This part of the paper compares the summary measures of MA and CA, and identifies their counterpart measures against which the discrepancies will be estimated.

Monetary Approach

The monetary approach to poverty measurement was spearheaded by Booth's seminal work in 19th century London, followed by Rowntree in the early 20th century. From a monetary perspective, poverty indicates a lack of the necessary income to purchase a minimally adequate basket of goods and services. This approach considers that monetary expenditures adequately reflect utility, and that utility is a satisfactory measure of well-being (Laderchi, Saith, & Steward, 2003). The validity of this approach involves a justification for defining both basic needs and a poverty line that sets the poor apart from the non-poor.

The monetary measurement, as a unidimensional method, typically adopts income and consumption as an indicator of well-being or resources. To construct an international poverty line that divides the poor and non-poor across nations, the MA employs an absolute international poverty line based on the costs of basic food, clothing, and shelter around the world. The cut-offs could vary by time and country. For cross-country comparisons, the global poverty line is set at $1.90 using 2011 purchasing power parity (PPP) as of October 2015.

By far, the most widely used summary measure is the Foster-Greer-Thorbecke (FGT) class of poverty measures. Foster, Geer, and Thorbecke proposed a general class of poverty indicators, the P_α class, also known as FGT, defined as $P_\alpha = \frac{1}{n}\sum_{i=1}^{q} [\frac{(z-y_i)}{z}]^\alpha$, where n denotes population size, z denotes a poverty line, and y_i denotes achievement (e.g. income). Among the FGT class of measures, incidence of poverty or the poverty headcount index, P_0, is the simplest and most commonly used poverty indicator. It indicates the share of the population whose income or consumption is below the poverty line. The poverty headcount ratio satisfies the focus axiom but violates both the monotonicity axiom and the transfer axiom. The depth of poverty measure (P_1) satisfies the monotonicity axiom, while inequality among the poor (P_2) satisfies the transfer axiom in addition to violating the focus and monotonicity axioms. All P indicators have the desirable property of being additively decomposable (de Janvry, 2016).

A primary policy solution suggested by the monetary approach is growing the income of poor people through economic development and redistribution. The main policy tools are associated with the economic sector including supports for energy, transportation, Information Technology, business services, construction, and trade. The eradication of extreme poverty as measured by the $1.25 a day headcount is at the top of the Millennium Development Goals (MDGs) and its successor, the Sustainable Development Goals (SDGs) established by the U.N.

Capability Approach

The capability approach constitutes an alternative way of conceptualizing poverty. In 1955, Arthur Lewis's statement that "development means widening the range of human choices" (HDR, 1996, as cited by Silber, 2008) was followed by the modern theory of capabilities advanced by Sen in his influential book "Development as Freedom" (1999), and can be seen in Nussbaum (2000)'s list of features essential to fulfill human life. The capability approach defines poverty as a failure to attain basic capabilities. A crucial issue in operationalizing the capabilities approach is deciding upon a set of capabilities, which is analogous to how the monetary approach makes budgetary determinations (Laderchi et al., 2003).

Multidimensional poverty measures incorporate indicators of the means and the ends of functioning. The Alkire Foster (AF) class of poverty measures, and the Multidimensional Poverty Index (MPI) as one notable application of the AF methodology, uses a set of ten indicators of well-being under three dimensions: two indicators for education (years of schooling, and child school attendance), two for health (child mortality and nutrition) and six for standard of living (electricity, improved sanitation, improved drinking water, flooring, cooking fuel, and assets ownership). To identify the poor, the AF methods use two forms of cutoffs considering depth and breadth of poverty respectively (Alkire and Foster, 2011a).

The aggregation step and key measures of MPI correspond to the technology and measures of the FGT. The dimension-adjusted FGT measures, denoted Mα is defined by $M_\alpha = \mu\ (g^\alpha\ (k))$ for $\alpha \geq 0$, where g^α denotes the 0-1, censored matrix of deprivations associated with y of the n (the number of people) by d (the number of dimension) matrix. M_0 is computed by multiplying the incidence of poverty H by the average number of deprivations each person experiences, A. *Multidimensional headcount ratio* H, comparable with *unidimensional headcount ratio* P_0, satisfies the focus axiom. H index is still meaningful when achievements are an ordinal variable while M_1 and M_2 do not share this useful property (Alkire and Foster, 2011b). M_0, is equivalent to the *poverty gap* P_1, and satisfies dimensional monotonicity. Table 1 compares the aggregation methods, axiomatic properties, and usage of MA measures against CA measures.

Table 1. The Comparison of the MA and the CA measures

Approach			MA			CA			
identification	Indicators of well-being		Income, consumption			Heath Education Public good			
	Cut off		Single			Dual			
Aggregation	Index		The FGT			The MPI			
	Class		P_0	P_1	P_2	H	M_0	M_1	M_2
Axiomatic properties	Axioms	Monotonicity	-	Yes	Yes	-	Yes	Yes	Yes
		Transfer	-	-	Yes	-	-	-	Yes
	Decom-position	Subgroup	Yes			Yes			
		Dimensional	-			Yes			
Usage	Data type	Cardinal vs Ordinal	Mostly use cardinal			Use both cardinal & ordinal data For ordinal, H & M_0 recommended			
	Intuitiveness	Conceptual calculation	Easy to understand			Complex matrix forms			

Advocates for CA consider long-term human development as a crucial means for improving livelihoods. The focus on human development policies is represented by the social sector. The most relevant sectors are education and health, but broadly include governance and civil society, population, water, or public goods and services. MDGs are explicit about multidimensional poverty enshrined in education, health, and environmental goals. Their successors, SDGs attempt to incorporate multidimensional poverty measures as a monitoring and policy tool. Under the first goal, SDGs target 1.2 states "By 2030, reduce at least by half the proportion of men, women and children of all ages living in poverty *in all its dimensions* according to national definitions." In sum,

Table 2 compares the MA and CA by their definitions, measurements, and policies.

Table 2. A Comparison of Two Approaches to Poverty

	The Monetary Approach	The Capability Approach
Definition	A lack of the necessary income to meet basic needs	A failure to achieve basic capabilities
Measure	The FGT ($1.90 a day poverty line) to identify the poor	The AF (Multidimensional Poverty Index) to identify the poor
	P_0, P_1, P_2 Food-based measure (consumption and income)	H, M_0, M_1, M_2 Living standards, Education, and Health
Policy	Growth and redistribution Economic development policy	Public infrastructures & services Human development policy
	MDGs and SGD's absolute poverty indicators	SDGs poverty indicators MDGs development dimensions
	Official Development Assistance towards economic (and production sector)	Official Development Assistance towards social sector

Choice of Measurement for Comparison

Based on the review of income and multidimensional measures, this paper proceeds to compare P0 and H. They are the most comparable measures given that they both concern frequency and incidence of poverty and satisfy focus axioms. The only difference between the two, is dimensionality where P0 has a single dimensionality, and H has three dimensionalities. An alternative strategy is to compare P0 ($1.90/day) and M0 as the two most popular indices representing the MA and the CA approach respectively, as seen in Alkire and Santos (2010). Such comparison highlights how poverty counting can be changed by adding "intensity of poverty" or simultaneous experience of deprivations on top of incorporating non-income dimensions. However, comparing the two measures, P0 and H, helps illuminate the question of how poverty is portrayed differently by taking into account non-income dimensions while holding other aspects constant.

The Overlap between Monetary and Capability Poverty Measures

Correlation between Poverty Indices

Between P_0 and MPI (H, M_0, and A). While all the poverty indices show positive associations with Pearson r above 0.50, there are differences in the magnitude of coefficients [See Correlation Matrix in Appendix A]. This paper reports Pearson r as Spearman shows similar results[1]. As income and multidimensional headcount measures are similar in terms of axiomatic properties, P_0 with H are the most highly correlated

[1] The Pearson's correlation coefficient evaluates the linear relationship between two continuous variables while Spearman rank correlation coefficient evaluates the monotonic relationship between two continuous or ordinal variables.

measures (0.77) followed by P_0 and M_0. It is also noted that H and M_0 are capturing similar aspects of multidimensional poverty with a coefficient of 0.98-0.99. The correlation between P_0 and intensity of poverty A (0.59) is slightly weaker than the correlation between P_0 with H. Scatter plots of poverty indices [shown in Appendix B] illustrate relationships among different poverty indices, which are roughly linear.

Between P0 and sub-dimensions of MPI. The second part of Pearson metrics presents correlation coefficients of P_0 and subdimensions of MPI – deprivations in education, health, and living standards dimensions. P_0 is highly correlated with electricity (0.78) and fuel (0.76) indicators of well-being under the living standard dimension of MPI. In contrast, the relationship between P_0 and the nutrition (Pearson's r: 0.52) indicator under the health dimension is marginally weaker than the correlation of P_0 and electricity/fuel pair. The correlation coefficient of the P_0-nutrition pair is less linear than the P_0-electicity/fuel pair given that the Spearman coefficient is higher than the Pearson coefficient by 0.09. The same argument applies to P_0 and the school attendance indicator under the education dimension given that Spearman's ρ is higher by 0.11 than Person's r, 0.55. The scatter plot matrices in Appendix B also confirm a relatively weak linearity of the poverty and nutrition/attendance pair than the poverty and electricity/fuel pair.

Fitted Lines between P_0 and H. Multidimensional poverty headcount is regressed on income poverty as specified in the equation, $P_{0_i}{=}\alpha + \beta H_i + \epsilon_i$. [2] Based on this specification, a 1% increase in multidimensional poverty is associated with a 0.64% increase in income poverty at a significance level 0.01. Adjusted R-squared is 0.59. The residual versus fitted values plot of this simple linear model shows that linearity and a constant variance assumption is valid. The plot is linear, clustered around 0 [Appendix C].

Linear line. Figure 2 displays the percentage of people under $1.90 a day against the percentage of multidimensional poor measured by H. The dashed line plots the 45° line, while the solid line plots the linear equation that best fits the scatter plot for each income group. The regression line runs below the 45° line, showing that in many countries more people are MPI poor than income poor, and a decrease in the percentage of MPI poor does not reduce the percentage of income poor at the same rate. The size of the bubble in the plot indicates gross national income per capita. Overall, low-income countries with small bubbles are located in the upper right corner of the plot, showing both higher income poverty rates and multidimensional poverty rates.

[2] Additionally, the log transformation of a dependent variable model, which helps satisfy the linearity assumption, is investigated as $P_{0_i}{=}\alpha + \beta ln(H_i) + \epsilon_i$. However, the results are similar.

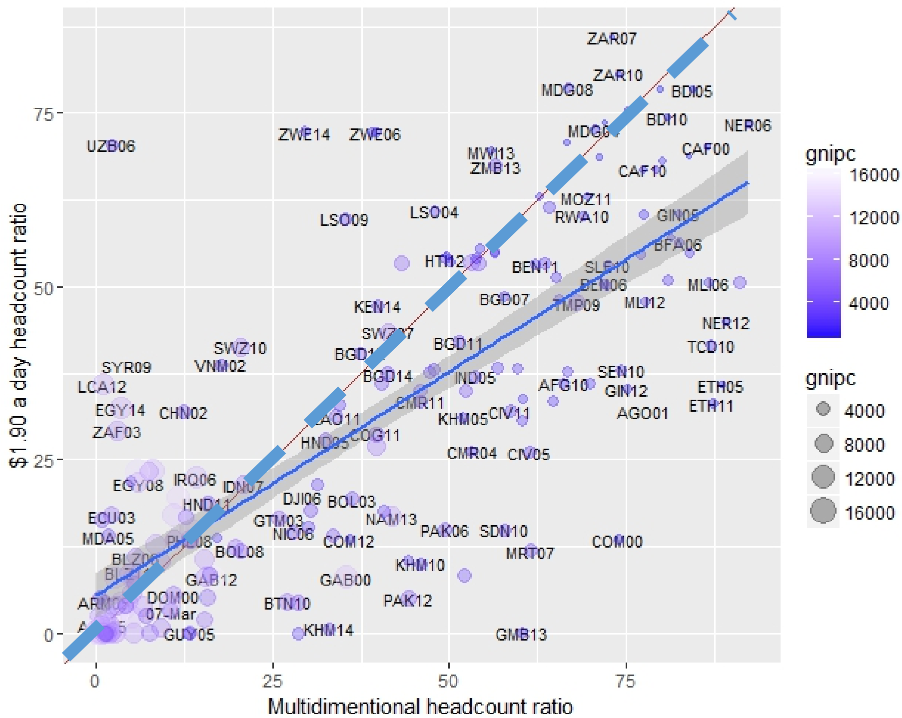

Figure 2. Scatter plot of MPI vs $1.90 headcount

By income group. Slopes and intercepts of the fitted lines differ by income group as seen in Figure 3. It suggests that lower-income countries (solid line) have higher intercepts and thus higher initial incomes and multidimensional poverty. The slope of the line is steeper in the lower middle-income country group (darker dashed line), implying that the percentage reduction in MPI poverty rates would be more strongly associated with a percentage change in income poverty rate among the lower middle-income groups than the low income (solid line) or upper-middle income groups (lighter dashed line).

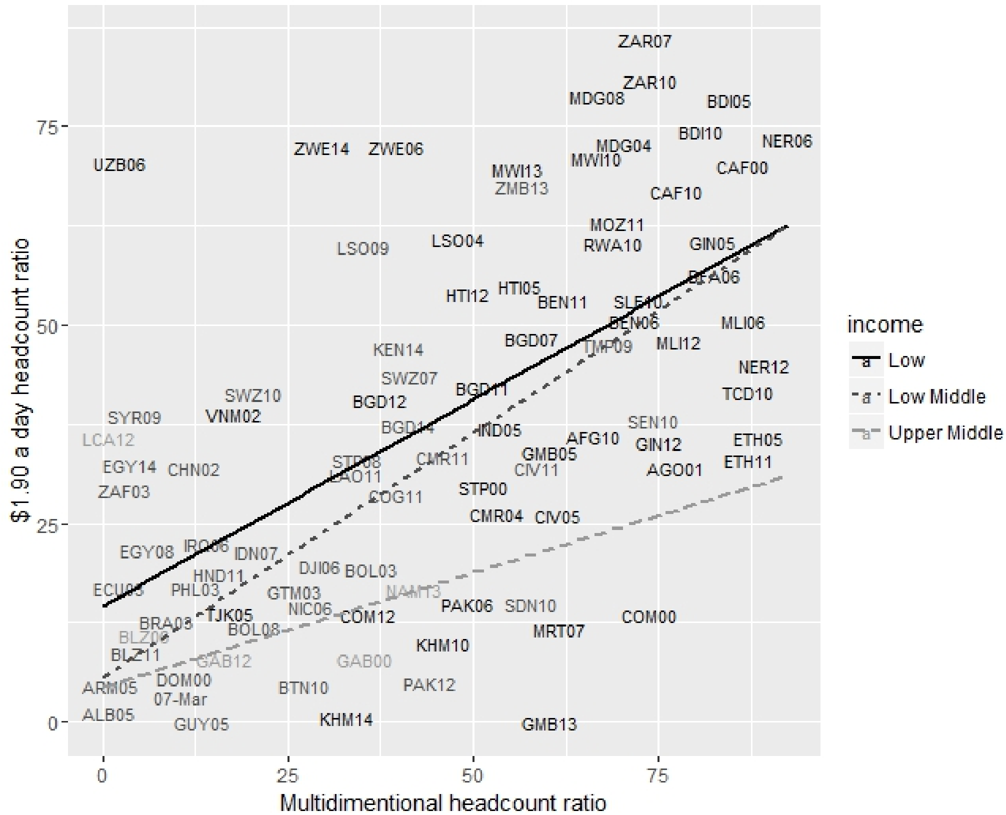

Figure 3. Scatter plot of MPI vs $1.90 headcount by income group

Non-parametric relationship. The relationship between income and multidimensional poverty is linear up from 0% to around 50%, but the line flattens out afterward where countries with higher poverty rates are concentrated. Figure 4 fits a smooth non-parametric curve to empirical data.

Figure 4. Non- parametric fitting

Findings from this simple correlation are corroborate with the literature (Roelen, 2017), suggesting that the monetary and multidimensional measures point towards a modest or even limited overlap of results. The analysis in this paper also reveals the incongruency between the two measures is more substantial for lower-income countries than lower middle-income countries. Low-income countries are considered to have higher needs, and effective action requires investigating such inconsistencies more in detail.

Classification of Countries by Discrepancy

The Degree of Discrepancy

This part of the paper further explores the magnitude of inconsistency by country. The residual (ϵ_i) of the linear fitted line for each country ranges from -44.45 (Gambia 2013)[3] to 63.51 (Uzbekistan 2006) with mean 0 and standard division 15.42 for 213 observations. Given that these are imputed data, they might not accurately reflect the gaps between two measures. When limiting analysis to non-imputed data [Table 3], countries like Cambodia, Nicaragua, or Senegal, capability poverty has higher H than P_0 while countries like Vietnam or Malawi have higher P_0 than H in absolute terms. On the other

[3] It is imputed value and should be taken with caution. Negative imputed values in the process of interpolation and extrapolation are forced to be 0 and may not reflect actual income poverty rates.

hand, countries such as Togo, Haiti, and Chad exhibit almost the same poverty ratio by both measures.

Table 3. Income and Capability Poverty

Country	Year	Discrepancy	Income poverty, P_0	Multidimensional poverty, H
Cambodia	2010	-25.12	9.97	45.9
Guinea	2012	-18.68	35.27	75.1
Nicaragua	2001	-14.14	17.59	40.7
Senegal	2005	-11.07	37.58	66.9
Mali	2006	-10.80	50.58	86.6
Mongolia	2010	-10.63	0.76	9.2
Morocco	2007	-9.18	3.12	10.6
Peru	2012	-8.10	4.13	10.5
Peru	2008	-7.65	7.94	15.7
Dominican Republic	2000	-7.16	5.46	11.1
Bolivia	2008	-6.78	11.91	20.5
Dominican Republic	2013	-6.42	2.32	5.1
Montenegro	2005	-6.17	0.25	1.5
Peru	2004	-6.08	12.22	19.9
Albania	2008	-5.98	0.37	1.4
Guatemala	2003	-5.67	16.51	25.9
Kazakhstan	2010	-5.46	0.12	0.2
Macedonia, FYR	2005	-5.30	1.38	1.9
Kazakhstan	2006	-5.22	0.62	0.6
Albania	2005	-4.98	1.12	1
Mexico	2006	-4.74	3.29	4
Mexico	2012	-4.58	2.68	2.8
Dominican Republic	2007	-4.08	4.34	4.6
Montenegro	2013	-3.95	1.69	0.3
Ecuador	2013	-3.22	4.43	3.4
Armenia	2010	-3.10	2.54	0.3
Congo, Rep.	2011	-2.38	28.71	39.7
Armenia	2005	-1.71	4.45	1.1
Colombia	2005	-0.99	10.4	9.2
Colombia	2010	-0.88	8.06	5.4
Brazil	2006	0.75	7.94	2.7

Honduras	2005	1.35	27.79	32.5
Brazil	2003	1.77	12.71	8.5
Honduras	2011	3.10	18.75	15.8
Philippines	2003	3.25	16.84	12.6
Nigeria	2003	7.00	53.46	63.5
Liberia	2007	9.01	68.64	83.9
Ecuador	2003	10.07	16.94	2.2
Rwanda	2010	10.24	60.25	69
Togo	2006	15.03	55.55	54.3
Haiti	2012	16.56	53.91	49.4
Chad	2003	16.87	62.94	62.9
Malawi	2004	21.62	73.63	72.1
Vietnam	2002	21.90	38.78	17.7
Malawi	2010	22.39	70.91	66.7

Country Classification

Each developing country can be classified into income poor and capability poor status, depending on the residual values between P_0 and H by year. Countries above the fitted line have positive residuals; they are relatively income poor (higher y value) compared to countries falling in the similar levels of MPI. Countries below the fitted line have negative residuals; they are relatively capability poor (higher x value) than countries with comparable economic standing.

Table 4 summarizes the number of countries falling into income poor, capability poor, and neutral poor categories depending on the threshold values [See Appendix E for the full data]. Overall, there are more capability poor countries than income poor countries. The strictness of criteria to be eligible for income and capability poor status increases to the right (column 2 < column 3 < column 4). According to the binary classification of countries into the income and capability poor group, out of 213 countries, there are 1.5 times more capability poor countries (127) than income poor countries (86). Countries can be divided into three categories: capability poor, poor, and income poor based on how far each country's data point deviates from the standard deviations. According to the binary and ±1 standard deviation (SD) criteria, Pakistan, Ethiopia, Cambodia, Nepal and Angola are experiencing capability poverty while Uzbekistan, Zimbabwe, Lesotho, Syria, and DR Congo are experiencing income poverty.

Using residuals (variable name *resid*) of the fitted line between the *log* of H and P_0 produces slightly different results. For instance, when using the log of H and $P_{0,}$ South Africa in 2012 is income poor while Gambia in 2005 is capability poor by the strictest ±2 standard deviation criterion.

Table 4. The number of Income vs. Capability Poor Countries by Year

	Binary classification	Countries with residual value of ±1 SD	Countries with residual value of ± 2 SD
Income poor	86	33	6
Poor	0	157	203
Capability Poor	127	23	4

Factors associated with discrepancy between income and capability measures

Additionally, this paper explores possible factors that help explain the discrepancy between income and capability measures using a non-parametric Random Forest model. By nature, residuals represent random variations in outcome variable unexplained by the model. However, one can still attempt to offer explanations for what drives the magnitude of residuals in both positive and negative directions. The analysis uses a Random forest algorithm with country characteristics that are not directly linked with indicators used to create the MPI or $ 1.90 a day measure. The variables with the largest mean decrease in GINI impunity is GNI per capita (20.4%) and life expectancy (10.27%). Interestingly, these two features of importance represent two crucial aspects of income and multidimensional poverty [For more detailed analysis see Appendix F].

Policy Implications

To exemplify potential applications of the discrepancy analysis, this section provides a snapshot of how discrepancies can inform sector aid allocation. The higher the residual (discrepancy) value, the more there is income poverty. The lower the residual value, the more there is capability poverty. If aid were to be responsive to the salient dimension of poverty, then income poor countries would receive a higher ratio of economic sector aid to social sector aid. In contrast, capability poor countries would receive a higher ratio of social sector aid to economic sector aid. This simple assumption can be tested using cross country panel regression. The question is how much of the variation in the ratio of social sector aid to economic sector aid is explained by the degree of income or capability poverty status.

The paper tests four models, depending on the incorporation of production sector and the estimators in panel regression. Model 1 (M1) and Model 2 (M2) only take into account the social sector aid earmarked by the Creditor Reporting System code. In contrast, Model 3 (M3) and Model (M4) include the production sector aid as a part of economic sector aid, assuming that production sector has a direct effect on ameliorating income poverty. M1 and M3 test fixed effect (FE) models within a country, ruling out the impact of time-invariant determinants of aid. M2 and M4 test random effect (RE) models across countries.

Control variables are intended to capture country characteristics [See Appendix D] for descriptive statistics and variable names]. Covariates are selected based on their potential influence on the overall size of aid and the sector composition of aid. Most research in this field finds that the population and GDP are among the most important contributors of average ODA per capita per recipient country (Berthélemy and Tichit, 2003; Nunn and Qian, 2014). The paper also considers the 0-6 scale and the overall Country Policy and Institutional Assessment (CPIA) score as predictors of governance sector aid, which is a subset of social sector aid. Volume-wise, aid to "government and civil society" sector has been the most important sub area of social sectors, which has led to the escalation of overall aid to social sectors in the past 15 years.

Additionally, time invariant regional dummy variables reflect heterogeneous development status across regions such as East Asia and Pacific (EAP), Europe and Central Asia (ECA) LAC (Latin America & Caribbean), SA (South Asia), and MENA (Middle East & North Africa). The variable takes the value one for that region and zero otherwise, with MENA serving as the reference for each dummy.

The paper takes a simpler and potentially more transparent approach. Studies show that dynamic panel models using mechanical instruments are unstable and potentially biased in finite samples (Roodman, 2009). Models in this paper thus do not adopt a dynamic panel model.

Model Specifications

The unit of analysis is the country (i), and measurement occasions (t) are nested within countries. There are total number of 66 country panels. The number of years (units) per country is minimum 1 to 4, spanning 15 periods from 2000-2014.

M1 and M3. The fixed effect models investigate occasion-level variation, assumed to be identical across countries. It represents the change of residual controlling for unobserved and observed country level heterogeneity over time.

$$\frac{social\ aid}{econ\ aid\ + production\ aid}_{it} = \alpha_i + \beta_1 resid_{it} + \beta_2 gnipc_{it} + \beta_3 policy_{it}. + \beta_4\, pop + \epsilon_{it}\ \ldots\ldots\ldots. (\text{For M1, production aid} = 0)$$

$$\sum_i \zeta_i = 0\,,\ \epsilon_{it} \sim N\,(o, \theta)$$

$$\alpha_i = \text{a fixed parameter constant over repeated sample}$$

$X_{it} = \{x_{1it} = gnip,\ x_{2ij} = pop,\ x_{3it} = policy\}$, associated vector β_3 can be written as β_{3a}, β_{3b}, and β_{3c}.

M2 and M4. This random effect model investigates mean effects of the residual on the ratio of social sector aid to economic and production sector aid across and within developing countries by holding everything else constant. It uses the regression equation below:

$$\frac{social\ aid}{econ\ aid\ + production\ aid}_{it} = \beta_0 + \beta_1 resid_{it} + +\beta_2 year_{it} + \ \beta_3 X_{it}. +\beta_4\ Z_i + \zeta_i + \epsilon_{it} \ldots (\text{M 2 , production aid} = 0)$$

$X_{it} = \{x_{1it} = gnipc, x_{2ij} = pop, x_{3it} = policy\}$, associated vector β_3 can be written as β_{3a}, β_{3b}, and β_{3c}

$Z_i\ (Time\ invariant\ covariates) = \{x_{4i} = EAP, x_{5i} = ECA, x_{6i} = LAC,\ x_{7i} = SA,\ \ x_{8i} = SSA\}$ associated vector β_4 can be written as β_{4a}, …. B_{4e}

$\zeta_i \mid X_{it},\ Z_i \sim N\ (0, \psi)\ \epsilon_{it}|X_{it}, Z_{i,}\ \zeta_i \sim N(0, \theta)$.

<Note> Regional dummy classified by the World Bank category: EAP (East Asia and Pacific), ECA (Europe and Central Asia) LAC (Latin America & Caribbean), SA (South Asia), SSA (Sub-Saharan Africa) MENA (Middle East & North Africa).

Results

Table 5 presents estimates for the four longitudinal models of sector aid responding to the income dimension of poverty. M 1 and M 3, which are the fixed-effects (FE) models, estimate the within-country effects of income poverty on social sector aid. M 2 and M4 refit model 1 and M3 with the random-effect (RE) estimator using the method of generalized least squares. Random effects models incorporate time-invariant variables and examine the mean effect of being an income poor on receiving different rate of social sector aid across countries.

The paper confirms the assumption of the RE model based on the results of the Huausman test. The Hausman test for the M1 (FE) and M2 (RE) pair, and for the M3 (FE) and M4 (RE) pair, are deployed as a test of the exogeneity assumption of RE models. The difference between the consistent but inefficient fixed model and the inconsistent but efficient random model is not statistically significant in either case. In the first pair and second pair, their Chi square test statistics with three degrees of freedom are 6.50 (p=0.08) and 3.58 (p=0.310) respectively.

As expected, the random effects models show that income poor countries receive less aid towards their social sectors relative to their economic sectors. In M2, a one unit increase in residual is estimated to a be -1.31 decrease in the rate of social to economic sector aid at a significance level of 0.05, holding control of other variables. The results indicate that capability poor countries receive more aid towards social sectors relative to economic sectors whereas income poor countries received a higher share of economic sector aid. When considering production aid as a part of economic aid in M4, the significant effect of income poverty disappears.

Regarding other variables, low policy score (CPIA) countries receive more aid to their social sector vis-à-vis their economic sector aid, specifically to the civil service and governance subsector. A one unit increase in the CPIA rating, which indicates good governance, is estimated to decrease social sector aid relative to economic sector aid by 67.33 at a p-value of 0.01. In M4, the magnitude of the effect of policy score is smaller (-6.068) than M2 (67.33), but its significance level increases to a p-value less than 0.001. All other covariates are not significant in random effects model.

Table 5. Sector Aid by Salient Poverty

The ratio of economic sector aid to social sector aid		Subject specific intercepts							
		fixed intercept (M1)		random intercept (M2)		fixed intercept (M3)		random intercept (M4)	
		$\frac{social\ aid}{economic\ aid}$		$\frac{social\ aid}{economic}$		$\frac{social\ aid}{economic\ aid + production\ aid}$		$\frac{social\ aid}{economic + production\ aid}$	
Name	Variables	Est	(SE)	Est	(SE)	Est	(SE)	Est	(SE)
fixed part cons		1007.1	(797.7)	254.4***	(76.47)	167.5	(78.32)	4.629	(14.98)
residv	degree of income poverty	-8.875	(6.310)	**-1.311***	(0.662)	-0.690	(0.620)	0.0284	(0.0407)
gnipc	Gross National Income per capita	**-0.106***	(0.0471)	0.00115	(0.00659)	-0.00161	(0.00463)	0.000332	(0.000405)
pop	population	-0.00000880	(0.0000159)	2.74e-08	(8.09e-08)	-0.00000165	(0.00000157)	2.04e-09	(5.00e-09)
CPIA	good governance score	-106.6	(153.1)	**-67.33****	(23.21)	-28.96		**-6.068*****	(1.423)
EAP	East Asia and Pacific			-52.66	(39.13)			12.38	(11.74)
ECA	Europe and Central Asia			-4.980	(39.05)			10.43	(9.379)
LAC	Latin America & Caribbean			40.02	(34.80)			10.19	(7.111)
SA	South Asia			-42.70	(39.48)				(.)
	Observations	66		66		66		66	

<Note: *p<0/05, ** p<0.01, *** p<0.001, Standard errors in parentheses>

Conclusion

This paper examines the discrepancies between global poverty measures in the identification of salient dimensions of poverty, with implications for need assessment and aid allocation. It finds that the two constituent approaches, MA and CA, differ in how they capture poverty and inform need. Although there is a moderate correlation between the poverty headcount ratio and the multidimensional poverty headcount ratio, some countries reveal large discrepancies. The degree of discrepancy characterizes poverty in each developing county. Countries such as Pakistan and Ethiopia are experiencing "capability poverty" while Uzbekistan and Zimbabwe are experiencing "income poverty." Out of 213 observations, there are 1.5 times more capability-poor countries than income-poor countries. The paper also finds that capability-poor countries receive a marginally higher rate of social sectoral aid, which aims to strengthen their capabilities, as compared to economic sector aid.

This study illustrates how incongruences in distinct measures of international poverty can be used to target, monitor, and evaluate global aid distribution. This analysis informs the balance between social and economic sector aid globally. Social sector aid aiming to address capability poverty has skyrocketed since the beginning of the 2000s, significantly outpacing the economic and production aid. Aid to the social sector, rather than showing a uniform increase across all countries under consideration, has gone up in those with relatively higher rates of multidimensional poverty than of income poverty. Further research can expand this discussion by analyzing whether the considerable policy shift favoring the social sector was in response to the growing rate of capability poor countries to income countries or the large magnitude of capability poverty as relative to income poverty. As for the individual country, more attention can be paid to outliers lacking the diagnosis and treatment match. For instance, Zimbabwe in 2016 received a higher ratio of social sector aid (USD 151) despite its income poverty status (discrepancy 41). In contrast, Sudan in 2010 received a lower rate of social sector aid (USD 6.77) despite its capability poor status (discrepancy -27).

This new tool can potentially address questions of responsibility with less shame and more dignity. Unlike income or development ranking described by high, middle, and low, there is no hierarchical relationship among groups in the suggested classification. Countries are measured relative to one another. Reflecting the strengths of each country rather than the weaknesses, the classification can be renamed, changing "income poor countries" to "relatively capable countries", and "poor countries" to "relatively higher income countries."

Different approaches to poverty provide policymakers and practitioners a better opportunity to target resources and track accountability. However, listing different poverty indices side by side for individual countries may not necessarily facilitate their full adoptions to policy-making decisions. There should be a means to integrate rich sources of data in a systematic but simple way. To that end, this paper estimates the degree of discrepancies, which can be called "the discrepancy index," systematically accounting for two major approaches to global poverty. For simplicity, this paper also focuses on two sectors of aid, economic and social, corresponding to income and capability poverty respectively. The analysis in this paper can be applied to give an overview of aid breakdown by sector, for instance, in the form of "Aid at a Glance" reports by the OECD and the UN. To conclude, this paper implies a potential way to holistically incorporate diagnostic tools that represent contemporary views towards global poverty.

CHAPTER 2: ALTERNATIVE MODELS OF COMMUNITY-LED DEVELOPMENT: IMPLICATIONS FOR POLICY AND PRACTICE

Introduction

A commonly-suggested way of improving the ownership and accountability of aid projects is to make them participatory (Mansuri & Rao, 2012). A project that is considered promising in applying these principles by most bilateral and multilateral aid organizations is participatory community development (Platteau & Abraham, 2002). Recent variants of community development allow community groups to make decisions about community development resources. These are labeled variously as community-driven development (CDD), community-driven reconstruction, sustainable livelihood projects, and social funds. To avoid confusion with projects branded by specific donors, the umbrella term for these activities in this paper is *community-led development* (CLD) projects.

The crux of the CLD approach is that the participation of the community comes early in the planning stage rather than later in the implementation stage. This enables project participants to make decisions about the type of project they would like to launch and implement. The choice of policy design that allows more user control is the funding arrangement; the form of block grants establishes policy within a given function and specifies the *broad* purpose of the project (Gilbert & Terrell, 2002). This "open menu" approach with a positive or negative list takes a middle ground in the continuum of control between the strict implementation of donor-initiated activity and unregulated activity.

Fragile States are contexts where CLD has been commonly applied as an example of "good international engagement in fragile states" (OECD, 2007, pg. 11) that support a broad state-building agenda. State fragility commonly relates to the state's failure to fulfill basic government tasks and the resulting loss of legitimacy and susceptibility to the insecurity of people (Jung, 2014). In fragile contexts, the pursuit of efficient disbursements of money and disapproval of a military dictatorship often require bypassing centralized public institutions, which may paradoxically undermine a country's ownership of the program and opportunities to build local capacities (Fritzen, 2007; Platteau & Gaspart, 2003; Bertoli, & Ticci,2012; François, & Sud, 2006). In reconciling the dual imperatives of legitimate state-building and efficient service delivery, indirect stewardship is becoming an important aid strategy to assist state-building processes (Batley & Mcloughlin 2010). The bottom line is that the government sets the rules and manages the finances, and it delegates the management of the program to civil society organizations, appointing an international agency to provide oversight services.

Nevertheless, a major challenge of the CLD intervention is a lack of both a top-down theory and bottom-up evidence. Increasing favoritism towards CLD in fragile states by development actors largely reflects normative benefits rather than a well-defined priori theory or strong ex-post impacts (Fritzen, 2007). Scholarship on decentralization provides important insight into the structure and rationale behind CLD,[4] aiming to increase "control" (Dongier et al., 2003; Mansuri & Rao, 2004; Labonne & Chase, 2011) and "power" (Dasgputa & Beard, 2007) of aid recipients. In practice, however, CLD is often delivered as a specific aid modality without a clear indication of the operational theories upon which it is built. Despite some common theories of change (Casey, Glennerster & Miguel, 2012 in Appendix G), numerous hypotheses and indicators, found in much CLD programming, seem to explore the reaches of program impact rather than reflecting an articulated logic of intervention.

Empirically, there are substantial variations among rigorous impact studies (Beath, Christia, & Enikolopov, 2013). In the absence of a rigorous meta-evaluation, this paper provides a matrix of the findings of primary outcomes of 11 rigorous impact evaluations conducted in the past decade across Asia, Africa, and, Latin America in Appendix H. It presents the divergence in findings across all three outcome areas: i) access to services and infrastructure, ii) household-level economic outcomes, and iii) social capital/coherence and local governance. In particular, evidence of impact on process-related, "soft social changes" is quite mixed with the five null results contrasting with four positive findings and one negative finding. [5]

How to explain inconsistencies among study outcomes is an important question to ask to justify expansion of the CLD. Not surprisingly, a mixed picture of CLD could arise from design parameters of interventions, the consistency and quality of project implementation (Fritzen, 2007), differences in country contexts, and time periods or research methods. However, these do not offer sufficient explanation, especially given that heterogeneity in outcomes is higher in some types of interventions than others. For instance, a synthetic review of Conditional Cash Transfers around the world reveals consistency and convergence in outcomes: robust effects on income/consumption, and only modest effects on final health and education outcomes (Fiszbein & Schady, 2009).

Another possible reason is the underdevelopment of a theoretically-based operational framework to compare contrasting CLD models. This proposition links the two interconnected issues of CLD interventions: the theoretical framework and the data-driven approach. A major challenge with CLD impact evaluations is that their outputs are diffused over a broad range of outcome indicators (Labonne, 2013). Without a guiding framework

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[4] Similar to the goals of decentralization, CLD intends to enhance i) civic engagement in decision making; and ii) better public service delivery and performance. The decision-making side of CLD can be defended on the grounds that it incubates political structures more accountable to poor and marginal groups in society (Johnson, Deshingkar & Start, 2007). When implementing CDD projects, disadvantaged citizens are encouraged to serve as a village development committee. Participating in decisions about the allocation of public resources also gives citizens "a clear stake in monitoring the implementation of those decisions;" and an enhanced ability to check the results of public expenditures (Evans, 2004, p.10). From the viewpoint of managerial efficiency, lower level administrative units close to citizens have better information and higher incentives to design and implement policies that respond to local needs (Steiner, 2007; Alderman, 2002). Indigenous groups are well informed about households in poverty, community preferences (Campbell & Brakarz, 1991), and can procure local goods and services at competitive prices.

[5] Among outcome domains, CLD seems to be slightly better at generating tangible, immediate outcomes (e.g., evidence on the access and utilization of health, education, and water) than long-term income outcomes or social and institutional outcomes. This finding is similar to White, Menon, and Waddington (2018)'s review of 25 impact evaluations.

on which parameters to measure and test, scholars and practitioners are left with the daunting task of evaluating the effects of open-menu projects. The examination of theories undergirding contrasting CLD models and their operationalization as aid projects helps identify critical dimensions empirical researchers need to experiment and modify according to the local context. While the domains of empirical evaluations are broad, discussions on CLD design concentrate on the issue of mitigating elite capture, as in recent studies such as Buntaine, Daniels, and Devlin (2018), Arcand and Wagner (2016), and Platteau and Gaspart (2003). Adding to the existing literature, the focus of this paper is to put forward less-explored building blocks of CLD designs.

The purpose of this paper, therefore, is twofold: i) to introduce a conceptual framework of CLD analysis to inform the design and evaluation of development projects, and ii) to present alternative CLD models drawn from two developmental approaches, which the paper uses for a comparative case study in Myanmar. Two on-going, multi-million-dollar CLD examples in Myanmar offer a rare opportunity to compare project designs shaped by ideologically distinctive institutional theories. Much of the revised neo-liberal thinking is reflected in the World Bank's National Community-Driven Development Project (NCDDP), while Korea's *Saemaul Udong* (SMU), meaning new (*Sae*) village (*Maul*) movement (*Undong*), reflects developmental state theories. The World Bank's trademark CDD has been a dominant block grant aid modality to communities. Compared to this established model, the Korean model reflects an strategy.

CLD aid to Myanmar has implications for the development community's response to fragile states.[6] Myanmar where 50 years of military rule led to a top-down structure of governance and international isolation, is now experiencing a burst of foreign public investment. Official Development Assistance (ODA) disbursements to the Myanmar government from the governments of donor countries reached \$7.3 billion (constant 2014 USD), more than a 1,348% increase from the \$504.2 million in 2012. CLD projects alone attracted more than \$600 million of foreign aid committed from 2012 to 2021. This paper presents policy implications to make large-scale CLDs more instrumental for building the capacity and legitimacy of the partner country.

This study draws from a review of project documents for SMU and NCDDP in addition to an analysis of geo-referenced sub-project data. This study is also based on interviews with state, international, and non-governmental participants held in Myanmar in April 2012, February 2014 and August 2015.[7]

[6] Myanmar is defined as a fragile state by the Country Indicators for Foreign Policy, the Failed States Index, the Index of State Weakness, the Global Peace Index, and the Harmonized List of Fragile Situations Fiscal Year 2012.

[7] They include the Myanmar Ministry of Agriculture and Irrigation (MOAI), the Ministry of Cooperatives, the Myanmar Agricultural Development Bank (MADB) in Nay Pyi Taw; the World Bank Myanmar Country Office, the UNDP, the Asian Development Bank; Pact, Good Neighbors, the Cooperative University, and residents of six villages in Yaungthangpin and Thanlyin townships. Interviews were also held with World Bank CDD Global Lead in Washington D.C. Headquarters, the Korean International Cooperation Agency's Myanmar Country Office and Sungnam Headquarters, and SMU project management and consulting agencies.

Analytical Framework

CLD Framework Drawn from Theories of State

I propose an analytical framework, the Agency-Power-Dimension (APM), to describe donors' general CLD aid policies in conjunction with specific CLD projects in Myanmar. The three components of this framework—agency, power, and dimension—correspond to the elements that characterize contemporary development approaches or ideologies: *agent, value,* and *policy*.

The concept of "development" is rooted in ideologies of what constitutes ideal institutions. A well-functioning state, as one of the most fundamental institutions, is a key for the welfare of the citizens and development of the country, and the evolution of major development approaches can be informed by the evolution of contemporary welfare state ideology. Figure 5 provides a general schematic of the ideology of development, drawn from welfare state ideology, and their main components: agent, value, and policy.

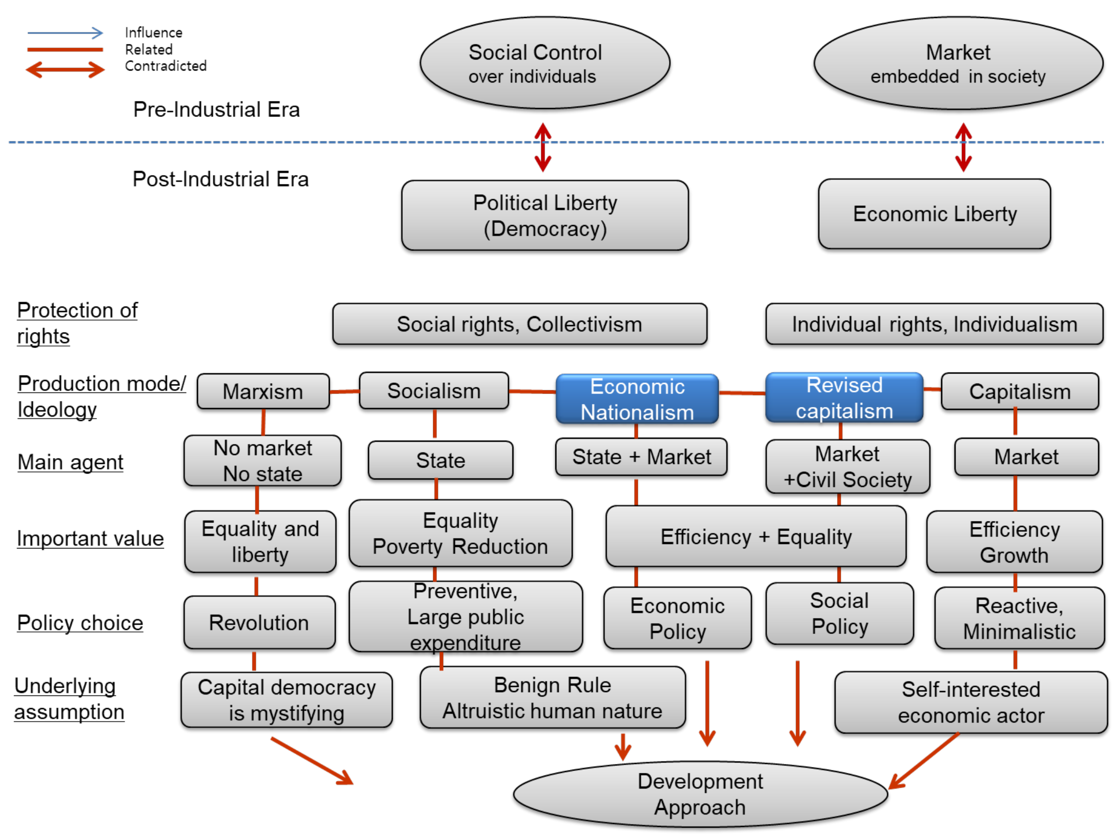

Figure 5. Evolution of Contemporary Development Approach

Ideal institutions conductive for development can be seen as a process of finding an equilibrium point between individual economic liberty and collective political rights. The tension between the two during the post-industrial era has involved ideological debates ranging from Marxism to capitalism. On the continuum of ideology, communism on the left is diametrically opposed to capitalism on the right. Ideologies in the middle, socialism, economic nationalism, and revisionist neoliberalism are closely related to contemporary development theories. The classification of Scandinavian/European aid, East Asian aid, and U.S. aid is in line with this ideological spectrum.

These conceptual elements can be reframed to more specific Agency, Power, and Dimension to fit into the CLD context. In the CLD context, the role of public or private *agencies* centers the debate around the change *agent*. The core of CLD interventions concerns how to promote *values* of efficiency and equity that are related to handling of *power*. The prioritized *dimensions* of development reflect *policy* choices in explaining the challenges and solutions of eminent problems the world is facing.

Agency-Power-Dimension framework

Agency, Power, and Dimension (APD) can characterize variations in participatory community development projects. *Agency* refers to the main agents of development in their role of delivering public goods such as state, market, and civil society. In providing undersupplied public goods, the question of who (e.g., state, market, civil society) should be the main driver and what their role should be in mitigating each other's failures characterize different approaches. *Power* is the strength and distribution of authority exerted by key agents. Power as "the currency that states use to achieve their desired ends" (Kohli, 2004, p. 20) can be differentiated in both quantifiable and distributional terms: how strong and how dispersed it is. A question arises as to whom the CLD project focuses on empowering. Empowerment aims to strengthen visions, capabilities, and the exercise of choice to achieve desired ends of agents. The design of the project also relates to a country's preference of political regime, government structure, and a base from which to draw legitimacy. Lastly, *Dimension* refers to collective development outcomes that link social and economic factors. The concern of major dimensions of development, and how they are related to each other underpins different operational aspects of a CLD intervention.

Donors Prototype Programs

There exists a demarcation between the revised neoliberal view and the developmental state approaches in addressing what constitutes effective aid in the field of community development. In the 1970s and 1980s, neo-classical political economy perceived the state as a problem rather than a driver of development. Seeking to explain the disappointing results of market reforms, a second generation of neo-liberal reforms views that the state must become an efficient market regulator (Krueger, 2000), considering institutions as important variables for economic growth (Acemoglu, & Robinson, 2012; Stiglitz, 2002).[8] These institutional approaches restored the role of the state to some degree by complementing the role of the market and civil society organizations in decentralization, the delivery of local public goods, and the provision of social safety nets. The Word Bank

[8] Despite a long history of institutional economics based upon institutions structuring markets and how this affects outcomes, it is relatively recently that mainstream economists have begun to consider institutions as important variables for economic growth.

has picked up on this theme, using the term “good governance” to refer to its new-found concern with how well states function in managing markets (Hira, 2009).

The developmental state model challenged the neoliberal “Washington Consensus” and diatribes against states’ economic role and public intervention. A pioneer in this model is Chalmers Johnson (1982). He was followed by many scholars such as Wade (1990), Amsden (1992), Evans (1995), Chang (1999), and Woo-Cumings (1999), all of whom applied this concept in understanding the economic development of East Asia in the late twentieth century. The developmental state is defined as a state that is focused on economic development and takes necessary policy measures to accomplish that objective (Johnson, 1982). Korea and other city-states such as Singapore, Hong Kong, and Taiwan provided examples of a new set of industrial policies that are paternalistic and aggressive but performance-based, giving competitive advantage to domestic industries.

Ideological contradictions have produced a divergence in CLD mechanisms or strategies among donors. This paper compares the norms and practices of traditional North Western views represented by WB CDD and those of an East Asian view represented by SMU in Korea, using the APD framework. The three elements of the APD are highly interconnected, but for the purpose of analysis, this paper considers them separately.

Agency

Neoliberalism. One could consider the role of NGOs as a "third way," and a "re-morphing of neo-liberal approaches" (Craig and Porter, 2003, p.54), serving mainly the purpose of a free market with little government regulation or institutional structuring. With the imposition of structural adjustment programs, financial institutions recommended the withdrawal of public expenditures, and NGOs filled the state vacuum providing for the underserved segment of the population. Local NGOs, however, may reinforce the dominant development paradigm. Relying on external funding from international foundations and multinational corporations, NGOs could serve the interests of the multinational capitalist class while creating standardized conditions for global market integration and capital flows (Wallace, 2009).

Ironically, local participation seems to increase, rather than decrease, the need for functional and strong institutions at the center. One of the generic dilemmas of participatory approaches is that such projects often demand more, not less, intensive agency presence (Mosse, 2005). As opposed to “shallow interventions,” which result in no substantial changes in political dynamics and development outcomes, the state has to commit to a long-term process of engineering to internalize change (Hoff & Stiglitz, 2001). There is little evidence that donor-funded, parallel project implementation units or agencies can substitute for a nonfunctional state as a higher-level accountability agent (Mansuri & Rao, 2012).

Developmental state. Developmental state theory would suggest that rather than serving the interest of the free market, civil society serves the national project of states, the most powerful of institutions. This view is consistent with its emphasis on the positive externalities of government - coordination and network over its negative externality such as corruption or rent-seeking. The state has strong capacity and presence in society to mobilize the overwhelming majority of the population to work and sacrifice for a revolutionary project (Woo-Cumings, 1999). Appealing to the shared virtue of self-help, the state steers non-partisan projects toward a depoliticized and new source of a national consciousness. As such it represents "a strange amalgam of egalitarian ethos, an ideal of social welfare and developmentalist dictatorship" (Han, 2004, p. 87). Saemaul Undong (SMU) in the 1970s in Korea provides an example of a domestically "induced participation." The National SMU was built on mobilization and direction from dictatorial leadership combined with gradually spontaneous cooperation at the village level (Reed, 2010).

However, martial law or authoritarian government means that CLD neither has a radically transformative intention nor is transferred to full-fledged political empowerment. Paradoxically, the economic success of these states has promoted the growth or emergence of active civil society, demanding democracy and transparency.

Power

Neoliberalism. Neoliberalism prefers a more even distribution of power to lower tiers of government, and a state's goals are drawn from a more multiclass base compared with a Developmental State perspective. Kohli calls this type of state in developing countries "fragmented-multiclass sates," one of the ideal-typical states to be found in the contemporary developing world. Deliberate democratic designs or weak political institutions encourage intra-elite divisions; legitimacy-sensitive political and economic elites only collaborate on some issues to meet the demands of numerous constituents. Attempting to pursue a complex agenda with limited state capacity may be less efficacious. However, they are not to be left unchecked by other political players. In the same sense, fragmented multiclass states draw their legitimacy from the process rather than from growth performance. Conventionally, reconstituting legitimacy in these states involves expanding participation and inclusiveness, creating accountability and combating corruption (Brinkerhoff, 2011).

Developmental State. The developmental states tend to have strong power concentrated at the apex. The legitimacy of the developmental state, or the "cohesive capitalist state," a term coined by Kohli, is drawn from the outcome of growth performance driven by political leadership and a professional bureaucracy. Both strong states and entrepreneurs pull the economy in the same direction toward state-defined goals. A narrow alliance of state and business elites with well-structured interest groups make others in society demand representation, which could diminish state power to pursue growth goals. Thus cohesive-capitalist states tend to be authoritarian, minimizing political opposition, and controlling the ideological mobilization of popular groups in the name of the nation. These states tend to equate rapid economic growth with national security and gain legitimacy in their pursuit of rapid growth.

Dimension.

Neoliberalism. The shift within a neoliberal development strategy from an emphasis on market deregulation and privatization to an extended emphasis on institutional reform is accompanied by interests in social and economic development (Mohan and Stokke, 2000). After largely unsuccessful structural adjustment programs, the architects of neoliberalism began to soften by acknowledging that development is a context-specific, socio-political process. This moved the neoliberal paradigm towards multiple stakeholder approaches involving partnerships between state, market, and civil society while giving a new life to the concept of social capital (Mohan and Stokke, 2000). This allows the major international financial institutions to stake out a development agenda based on Keynesianism (Fine, 1999).

Social capital, in particular, has become central to the outcomes of development projects whose unit of intervention and measurement are found at the community level. Defined by theorists such as Bourdieu, Coleman, Putnam, and Burt, social capital is multidimensional in nature, but its general property is related to the resources accruing from network relations as highlighted by Van Der Gaag and Snijders (2005). The neoliberal view of social capital in particular is presented in a neutral language. For instance, "collective action" and "trust" are the two common measures of social capital appearing in three CDD studies, Labonne & Chase (2011), Grootaert et al. (2003), and Wong (2011), related to the World Bank [Appendix I]. Just like monetary capital, social capital is perceived as something good in nature, and more conflict-oriented notions of power, class, gender, and ethnicity are rarely used.

Developmental State. The developmental state seeks one goal at a time, and if successful it builds upon it. This contrasts with a neoliberal approach that requires setting up an overarching macro frame and simultaneously pursuing multiple reinforcing goals (Kohli, 2004). The developmental state aligned narrowly with producer groups has a narrow commitment to economic growth. Therefore, social development is perceived as a means to achieve economic prosperity. The interpretation of social capital, therefore, goes beyond a cooperative mode of collaboration and includes competition in a way that can harness resources and incentivize performance.

Community-led Development in Myanmar

Institutions of donors are mirrored in CLD aid operations in two contrasting community development examples in Myanmar. Korea's Saemaul Undong project (SMU; 22 million 2014-2019) showcases an alternative model as compared to the World Bank's National community-driven Development Project (NCDDP; 86.3 million 2012-2019). The two cases illustrate the way in which abstract concepts of institutional theories shape donors' different approaches to CLD, and then are filtered into concrete operational guidelines of CLD aid. My analysis is anchored on the APD framework developed in the previous section.

Agency: Public vs. Private

The private CLD project intends to fill service delivery gaps where markets are missing or imperfect or where public institutions fail to fulfill their mandates. SMU carries out the delivery of services through quasi-governmental agencies; the NCDDP depends heavily on the market actions by private companies or international NGOs.

The role of the central government and political leadership. The Myanmar SMU project emphasizes the commitment of political leadership and central government to drive and sustain the project. The SMU Master plan highlights the "strong commitment and role of government," stating that "governments' intervention plays important roles for securing fast, strong, and continuous social change as well as the grassroots' behavioral changes" (p. 209). The SMU master plan also lays out its plan to set up a presidential advisory committee, affirming the importance of political leadership. This view highlights the positive role of government in promoting coordination and network externalities.

At the other end of the spectrum is the view represented by the NCDDP. It concerns the negative externalities of government corruption and rent-seeking. The WB report (2012) makes it clear that bringing in new stakeholders in the local development process will broaden the coalition for change and help build public confidence in the country's transition from a long period of authoritarian rule. It states that "fifty years of military rule led to a top-down structure of government" (2012, p. 2). The World Bank's solution to the top-down structure is "going local," which reinforces President Thein Sein's call for a "paradigm shift to a people-centered, bottom-up approach." This reaffirms the benefits of decentralization, describing that "While formal governmental structures and authorities have been predominantly top-down, governance at the local level offers more entry points for accountability" (p. 3).

Role of non-governmental actors. SMU carries out delivery of services through quasi-governmental agencies whereas the NCDDP depends heavily on the market - private companies or international NGOs. SMU is characterized by the strong degree of involvement from the Department of Agriculture (DOA) of the Ministry of Agriculture and Irrigation (MOAI) from the Union government to village-level SMU committees. At the lowest level of operation are agricultural extension workers, demonstrating SMU's focus on working with the government. The main project implementer is also the quasi-government organization from Korea. Because the overarching strategies of the project were built upon Korea's *Saemaul Undong* in the 1970s, technical assistance to the Union-level DOA is delegated to Korea's quasi-government contractors such as the Korea Rural Community Corporation (KRC). The KRC is also in charge of providing training for local civil servants and villagers in collaboration with the Korea Saemaul Undong Center.

The role of Western non-government actors is predominant in the process of decentralization promoted by NCDDP. Overall, the World Bank has contracted firms and NGOs based in the Western countries to provide technical assistance to the Department of Rural Development (DRD) under the Ministry of Livestock, Fisheries and Rural Development (MLFRD) at the central and local level. Hired firms and NGOs are mostly from Anglo Saxon or European countries. For instance, the union levels consulting service was contracted out to an Italian Agriconsulting company in partnership with Vietnamese and Indonesian companies in 2013. The role of non-government actors prevails at the lowest level as well. NGOs or consulting firms at the township level recruit community facilitators, mostly young women in the 20s native to the township, to train villages rather than provide direct trainings for villagers.

Power: Bureaucratic Efficiency vs. Democratic Legitimacy

SMU relies on strong and committed village leaders and civil servants as change agents. Outcomes of the project legitimatize project investments. Therefore, the pilot project focuses on building "model villages," and scaling them up, rather than targeting poverty reduction in poorer regions. In contrast, the World Bank focuses on a more even distribution of power. The legitimacy of the project depends on a process of broadening class alliances or, in order words, facilitating participation of marginalized groups. For this aim, it puts in place a mechanism of inclusion and equity.

Empower whom? The Burmese SMU intends to take advantage of a "potentially benevolent form of elite domination" (Rao and Ibanez, 2005) when hereditary, more educated leaders motivate the participation of villagers and improve project maintenance. Eligibility criteria for the SMU committee indicate the project's focus on high caliber leaders. SMU Committee members should be healthy in working age, be literate, and have a track record of involvement in development activities. SMU provides centralized training for village leaders and civil servants in a central training center in Nay Pyi Taw.

In contrast, the NCDDP puts in place multiple mechanisms to mitigate elite capture of processes and outcomes at the community level. The emphasis on women's leadership in key positions is stronger in the Village Project Support Committee (VPSC) than Saemaul Undong Committee (SMUC) while the eligibility requirement for the (VPSC) position is less strict in the VPSC than for the (SMUC). The VPSC must be headed by one man and woman, and at least one of the members of each subcommittee must be a woman whereas SMUC allocates 30% of positions to women. Another social accountability measure is a grievance redress mechanism (World Bank, 2012) to support voice and accountability of excluded groups. Regarding training, the curriculum for villagers is decentralized; it is carried out by individual NGOs and firms in charge of particular townships.

To whom? Targeting. The purpose of the SMU project is to create a success story and scale it to the national level. Thus, selecting accessible pilot villages where other villages can visit and follow their footsteps was considered important. Taking into consideration the potential for project performance, an initial 127 and final 100 pilot SMU villages were selected based on administrative targeting. Forty percent of weights are given to factors related to the project's outcomes: the existence of village leaders (20%) and the preparedness of villages for the project (20%). The rest of the weight is placed by accessibility, the presence of an urgent need, and topographical representation.

Comparatively, NCDDP considers poverty rates, capacity, an absence of external funding/ conflicts, and proximity to the aid offices, based on both administrative and self-targeting. The selection of the CLD project was made through broad stakeholder consultation that is considered effective in identifying the poorest townships in the absence of quality data.

Where? Space. SMU and NCDDP define the boundaries of communities differently. The two projects have different units of intervention. SMU emphasizes social ties, corresponding to Mattessich and Monsey's (2004) definition of people living in set geographical locations who are linked by close social ties. Thus, naturally evolved units of communal living, the village, becomes the basic operational level of the project. On the other hand, WB NCDDP emphasizes administrative units, highlighting a boundary of resources and capacity required to meet local needs, which Matarrita-Cascante and Brennan (2012)'s research points out. The main decision-making authority for the NCDDP block grants lies within the village tract level, which comprises several villages. Village tracts may be more reliable development partners, equipped with workers and accounting systems.

Dimensions: Economic vs. Social Development

Although both SMU and NCDDP use open menus with some guidance and restrictions, the SMU project prioritizes income generation, and NCDDP centers on access to basic social services and the enhancement of resilience. Accordingly, SMU recognizes competition among villages as a valuable component of social capital outcomes. This perspective contrasts with the NCDDP's view of social capital revolving around the concepts of collaboration and cooperation.

Main sector and menu. SMU is characterized by its focus on economic dimensions. One of the two substantive areas of SMUC is income generation. It is a main goal in the second phase of prototype Korea SMU. In this view, village sub-projects should be directed to invest in micro-enterprises and facilitate introduction of farming/processing technologies, mostly through microfinance. The income generation activities should be related to the improvement of agricultural products, animal breeding, and off-farm income diversification. In contrast, the importance of the human development dimension in the NCDDP resonates within its operation manual: "This people-centered shift holds out the promise of change in greater proportion of government budget to health and education" (World Bank, 2015, p. 1). As such, key substantive areas aim to reduce poverty by improving basic public infrastructure and social services along with inclusion of the vulnerable populations in the village.

Partners. Such differences in the main dimension of intervention relate to the expertise, adequacy of the staffing, and ability for intra-ministerial coordination of the respective line ministry. SMU's partner, Department of Agriculture (DOA) of the Ministry of Agriculture and Irrigation (MOAI), has long-standing expertise and presence across countries in agricultural production and income. Sub-areas include primary productivity at the farm level, agro-based small to medium enterprises, and the agricultural supply chain. The choice of Department of Rural Development (DRD) of the Ministry of Livestock, Fisheries and Rural Development (MLFRD) by the World Bank as the partner agency reflects the ministry's track record in supporting construction of small local infrastructure, especially rural feeder roads and bridges, and the provision of water supply and rural electrification. DRD with its two township offices, one administrative and one engineering, has engineering capacity and a presence.

View on social capital. SMU is designed to leverage inter-village competition as economically valuable social capital. SMU does this by scaling up the number of block grants for well-performing villages. On average, SMU not only gives larger funding amounts per village than the NCDDP, but also rewards outstanding villages with additional resources in the next project cycle. Villages receive USD 20,000 in the first year. After that the State/regional SMU Committee and the Central SMU committee review the performance of 100 villages, dividing them into three groups (each 33%), and payment is commensurate with the grade A, B, and C. In year one, the amount by the grade differs by USD 10,000; and in year two, the difference doubles.

NCDDP's view presents a narrative of collaboration that values equity; benefits should be allocated so as to equalize the distribution of resources and opportunities across villages (Gilbert and Terrell, 2002). NCDDP does not link sub-project performance with the size of the grant in the subsequent years. The average block grant allocations of NCDDP are based on the population of village tracts and tend to be larger in the second phase. Assuming that one village tract is composed of an average 6.5 villages, block grants per village range from average USD 4,153 (min USD 232 – max 12,810), which is significantly less than the average SMU funding.

Table 6 summarizes the comparison of SMU and NCDDP. The two programs (columns) are compared against the Agency-Power-Dimension framework (rows). The column side is further broken down to i) underlying ideologies that shape donors' CLD prototypes, and ii) the aid project design in Myanmar.

Table 6. Comparative Analysis of NCDDP and SMU

Framework	Types of CLD	World Bank CDD		Korean SMU	
		Theory	Aid Project	Theory	Aid Project
		Revised neoliberalism	NCDDP in Myanmar	Developmental State	SMU in Myanmar
Agency	Main Agent of development	Market	International NGOs	State	Government extension workers
	Central government interventions	Corruption	Limiting	Coordination	Supporting
Power	Strengths and Distribution	Democratic	Curb elite capture	Authoritarian	Benevolent elite domination
		Decentralized	Decentralized training	Concentrated	Centralized training
	Source	Procedure	Poverty-based targeting Administrative boundary	Performance	Capacity-based targeting Kinship-based boundary
Dimensions	Objectives	Social Development Equity	Infrastructure	Economic Development	Production
	Linkage between social and economic goals	Collaboration	Population-based funding	Village competition	Performance-based funding

Conclusion

This study finds that the intervention strategies of SMU and NCDDP differ concerning the main agency of change, handling of power, and objectives of projects. SMU deploys quasi-governmental agencies from Korea to train local government extension workers. In contrast, the NCDDP emphasizes the role of the free market with private companies or international NGOs hiring facilitators to train villagers. The two projects also have contrasting views on the source of power. The success of SMU depends largely on the outcomes of local projects, whereas NCDDP focuses on the processes of equity and inclusion. Last, SMU is dedicated to economic development in local communities, with an emphasis on agricultural production and related income generation. NCDDP's efforts focus on the dimension of social development in the context of public infrastructure development.

Discussions on the building blocks of CLD interventions help focus evaluation efforts of CLD with implications for development efforts elsewhere. Given the nondeterministic nature of CLD subprojects, impact evaluations use a large number of indicators, and the effects of the overall CLD projects tend to be diffused over a broad range of indicators. This diffusion presents a challenge in adequately estimating CLD effects, and so this study identifies important areas that experimental studies need to analyze.

The APD framework provides key design parameters of the CLD intervention that need to be further investigated. Thus far, CLD evaluations focus on exploring overall impacts in three areas, based on the logical progression of the intervention: local services and infrastructure, economic outcomes, and institutional outcomes. In addition to the overall outcomes in these domains, one of the vital evaluation questions is how CLDs can be structured to maximize stated goals. In order words, how do outcomes vary with the three key design parameters of agency, power, and dimension? Each facet of the APD framework can be used as treatment arms in experimental studies. The CLD interventions and evaluation might contain the following elements in their experiments:

- The use of private community facilitators vs. the use of agricultural extension workers
- Equal-sized or population-based funding vs. performance-based funding
- Centralized vs. decentralized training
- Unit of intervention at the village (kinship-based) level vs. administrative level
- Open menu concentrated on social sectors vs. open menu concentrated on income generation.

Within the limitation of a case study, CLD projects in Myanmar showcase that donors' own institutional models play an important role in shaping their development approaches. With the rapid deployment of CLD projects driven by donor agencies, both SMU and NCDDP did not grant high-level policy discretion over the Burmese government, but outsourced policy design functions to foreign organizations. The World Bank, like many Western donors, needs to acknowledge the different conditions of authoritarian regimes in South Asia, recognizing "what there is to build on" rather than taking good governance as a starting point (Grindle, 2011, p. s208; Booth, 2001). Likewise, the domestically mobilized Korean Saemaul Undong, in the presence of unusually strong political leadership and double-digit growth, might not be easily replicated in other developing countries.

A new approach can encapsulate insights from the West and the East by either synthesizing or sequencing different approaches. Instead of reducing the scope of the state with privatization, an alternative approach can pay attention to the development of state strengths. The central and local government can play more proactive roles in leading CLD projects in their nascent stages, and eventually give way to private organizations as the project is stabilized and scaled up. This hybrid strategy would also benefit from taking into account the rights and voices of underrepresented groups in development processes and outcomes while incentivizing good performance measured against baselines. The sequential policy implementation of CLD can be accomplished through two broad phases of a main menu: first a few cycles focusing on infrastructural development and later cycles moving to income-generating activities.

The paper also informs policymakers about the need for countries to integrate specific economic, social, and ecological goals. Identifying the "right institutions" is context-and time-specific. Existing models can offer inspiration to policy makers and a framework for building rural development strategies in the Global South. However, the partner country must be able to take advantage of alternative policy options and apply them to unique domestic settings and to the changing context of international development.

CHAPTER 3: MAPPING COMMUNITY DEVELOPMENT AID: SPATIAL ANALYSIS IN MYANMAR

Background

Aid policy has the potential to alleviate global poverty by targeting areas of concentrated need. However, a gap exists between aid given and actual need because of inadequate data and problems with delivering aid in conflict-prone areas. Evaluations of need have traditionally relied on costly and time-consuming survey techniques. These difficulties are exacerbated in conflict-prone areas of development. Although the share of the world's poor remains high in fragile states, on-going civil strife, armed conflict, and population displacement represent challenges to deliver aid directly to the poor. Often little or no ground-truth survey are available on income and wealth in sub-national regions where aid projects are taking places. Thus far, few aid-determinant studies have analyzed the characteristics of poverty at the sub-national level. This study intends to fill this research gap by using spatial analysis to estimate poverty in small regions in Myanmar. This approach allows policymakers to identify poverty at a policy-relevant and granular level and promote targeting, monitoring, and evaluation of aid for the most marginalized populations.

This paper explores the sub-national distribution of poverty-oriented and participatory interventions, called community-led development (CLD) in Myanmar. CLD intends to improve the ability of the poor and marginalized to contribute to and benefit from development processes and results. It allows community groups to make decisions about development resources often in the form of a block grant. This aid modality is commonly practiced in countries transitioning from authoritarian government to democracy.

Myanmar is one of the poorest countries in Asia. Approximately 26% of the country's 51 million people live in poverty.[9] CLD is in line with the government's efforts to reduce poverty by improving agricultural productivity and developing transportation and electricity infrastructure. It does so by reaching the poorest villages and addressing the needs in basic infrastructure and social services where governments have failed to fulfill their mandates and markets are imperfect or missing. This important targeting assumption behind the CLD, which makes the intervention "accountable to poor and marginalized groups," has not yet been tested empirically.

CLD is not a homogenous policy instrument. Two variants of CLD in Myanmar, the Korean International Cooperation Agency (KOICA)-supported *, NCDDP* and the World Bank-supported National Community-Driven Development Project (NCDDP), embody different targeting strategies. SMU prioritizes existing capacity whereas NCDDP focuses on poverty. In SMU's geographic targeting, 60% of weights are given to potential outcomes such as community's organizational capacity and accessibility to regional market,

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[9] The country's GDP per capita is estimated at $ 6,300 in 2017, and its growth rate has been volatile between 6% and 7.2% during the past few years.

while 20% of weights are given to a topographical representation[10] and the remaining 20% to the presence of an urgent need. On the other hand, NCDDP targets areas which are considered to be most in poverty and do not have external funding. Additionally, capacity-related criteria are in place including the willingness of the community, commitment by the regional government to the objectives of the project, and an absence of conflict (World Bank, 2012). The distinctive selection criteria of two aid models hints that the NCDDP goes to poorer areas but avoid conflict-prone zones. On the other hand, SMU would be placed in less deprived areas but closer to conflict zones.

The goal of this study is to test assumptions about CLD targeting empirically. It first examines whether CDL responds to sub-regional needs and second assess differences in the two CLD models in terms of their spatial placement.

The main research questions of this study are:

- Question 1: How much of the variance in CLD projects is explained by poverty?
- Question 2: To what extent does the targeting of the two CDL models (SMU and NCDDP) reveal differences in their orientation toward poverty?

This paper builds upon existing literature to develop measures of need and aid quantity for small communities. Aid determinant studies adopt different identification strategies, but mostly focus on the national-level characteristics of the recipient country to explain differences in aid volume. Setting aside allocations of aid on the basis of commercial and strategic interest of donors (Alesina and Dollar, 2000), population and lag GDP/GNI are among the top contributors of average Official Development Assistance (ODA) per capita (Berthélemy and Tichit, 2003; Nunn and Ac, 2014). In these studies, aid quantity is measured by annual per capita net or gross aid volume, and poverty is measured by national income of a recipient country. The issue is that even if more aid is going to low-income countries, it may not necessarily reach the most impoverished communities within a country.

Among sub-national level analysis, Brigg (2013) examines how aid targets sub-national wealth, using 1,400 geolocated aid projects by the World Bank (WB) and African Development Bank (AfDB) in 17 African countries in 2009-2010. The author measures aid in three ways: the region's share of a country's total number of aid projects, weighted aid projects by their costs, and the natural log of the total dollar value of each region's projects. The results reveal that regions tend to receive more aid when they have more people in higher wealth quintiles. Similarly, Findley et al. (2016) find little evidence that a higher frequency of co-financing activities between the WB and AfDB in six African recipient countries achieves better aid targeting. The studies introduce a novel approach that considers variance in geo-referenced aid location. One of the limitations, however, is that the unit of analysis in these studies is at the state-level boundaries (administrative level 1)

[10] Topological quota consists of hilly region (upland crops), plain/dry/delta(paddy), and seashore (fisheries) to draw lessons from various localities.

of countries, which does not give enough information on the targeting of smaller administrative levels. Relying on a formal administrative level could also exclude communities unincorporated from official administrative boundaries. Both studies are also restricted to the financial dimension of multilateral organizations in African countries.

I conduct analysis at the smallest geographical unit at the village level, or, at the administrative level 5. One of the measurements of this study, aid hotspots, does not depend on administrative boundaries. Thus far, research has drawn from georeferenced aid locations from AidData website that are not up-to-date and fine-grained. For instance, AidData gives only 14 data points for NCDDP projects at the township centroids by the year 2014. In contrast, web scraped aid data in this study gives the finest and the most current location data for more than 12,000 project sites at the village centroids. While analyses in this field have examined all aid projects, this analysis is intentionally restricted to specific interventions that are intended to target poverty because not all the projects target poor regions. For instance, it might not be feasible to place hydropower dam projects in the most impoverished regions. Departing from literature that focuses on multilateral aid to Africa, this study covers activities of both multilateral and bilateral donors in the relatively unstudied country of Myanmar.

This research adds to the literature of exploiting remote sensing techniques for estimating poverty. Poverty in this paper is examined in more than one way. Poverty measures are different from other similar measures because they reflect income distribution and confined to the conditions of the poor. Wealth and income indices aim to measure trends found in the population as a whole. However, the concept of poverty here is understood in relation to wealth, vulnerability, and socio-economic development indicators. Despite different views of needs each concept represents, poverty in this paper is used interchangeably with other terms, referring to disadvantaged conditions requiring more assistance. This allows the author to synthesize diverse aspects of poverty derived from various sources.

This work uses nighttime as a proxy for socioeconomic development associated with regional aid allocation. Studies have found a strong correlation between luminosity at the national level and standard measures of economic output such as Gross Domestic Product (Doll, Muller and Morley, 2005; Chen and Nordhaus, 2011) and growth measures (Henderson, Storeygard, and Weil, 2012). While mobile phone data has strengths in conducting micro-targeting of *individuals and households* (Blumenstock, 2016; Milusheva, 2016), satellite data demonstrates a reasonably accurate prediction in measuring *sub-regional* wealth across communities. There is some skepticism of using direct nightlights measures for the livelihoods of the very poor along with recent movement towards transferred learning (Jean et al. 2016) or unsupervised learning approach using daytime imagery (Jean et al., 2018). However, from a cost-benefit perspective, nightlights still provide the benefits of a reasonably accurate estimation at a low computational cost in comparison to daytime satellite imagery, thus giving a practical option for policymakers who might be more interested in making a plausible assessment.

The main contribution of this spatial study is that it helps to assess the match between need and policy response, and it creates a high-resolution map as a design and monitoring tool for CLD interventions. Studies on the sub-national variation in the distribution of child mortality, disease or endangered species have been influential for targeting resources and policy design within and across countries. Adopting methodologies developed in the field of health (Burke, Heft-Nealand Bendavid, 2016) and conservation science (de Boer et al., 2012), I spatially interpolate wealth fields onto aid locations. This match allows statistical analysis of factors explaining aid presence and density at the community level. An approach developed in this study can be replicated to understand potential drivers of community interventions in hard-to-reach contexts.

Methods

Data Sources

This study is based on six sources of data: aid data from web portal interface and administrative documents; wealth, water, climate, population data from the nationally representative survey; satellite imagery of nightlights; conflict event data; vulnerability data, and Myanmar's administrative boundary data [Table 7.]. There are many varieties in the names of administrative units both in English and in Burmese and they changed over time For instance, Mong Kung township in Shan State is also called Mongkung, Mongkaung or Möngkung. In 1989, the city of Tavoy's English name was changed to Dawei. Thus, merging of some dataset based on the names of administrative units as a unique identifier requires manual review and classification. Each data source is described below along with how it is collected in the study.

Community development aid data

This study covers all 12,282 CLD project villages in Myanmar in year 2017-2018. From 2012 to 2018, the NCDD project was cumulatively rolled out, and this paper uses the 12,182 locations available to web scrap. The SMU project has been taking place in its selected 100 villages as of 2013. NCDD project implementation data were gathered through automated web scraping from the management and information system website. The web portal displays many layers of project maps horizontally and vertically, including 1 union, 15 state/region, 61 township, 2,677 village tract, and 12,041 village-level maps.[11] A Python library, Beautiful Soup, is programmed to loop through each layer of the map vertically and horizontally and gather latitude and longitude coordinates of all project villages [Figure 6]. A list of SMU villages is drawn from the 2016 SMU project monitoring document, and the names of the villages are used to find the centroids of each village automatically either by an ArcMap tool or manually.[12]

[11] Based on t2017-2018 (year 5) data. The number of villages is slightly different from the database on the web.

[12] As there are many variations in names of administrative units written in English, some village names were not matched with any geo-coded locations. Their names have also changed over time in Burmese. In these cases, village names were manually matched with centroids of official and updated English and Burmese names Myanmar Information Management Unit based on similar phonetic sounds and historical records of changes in names.

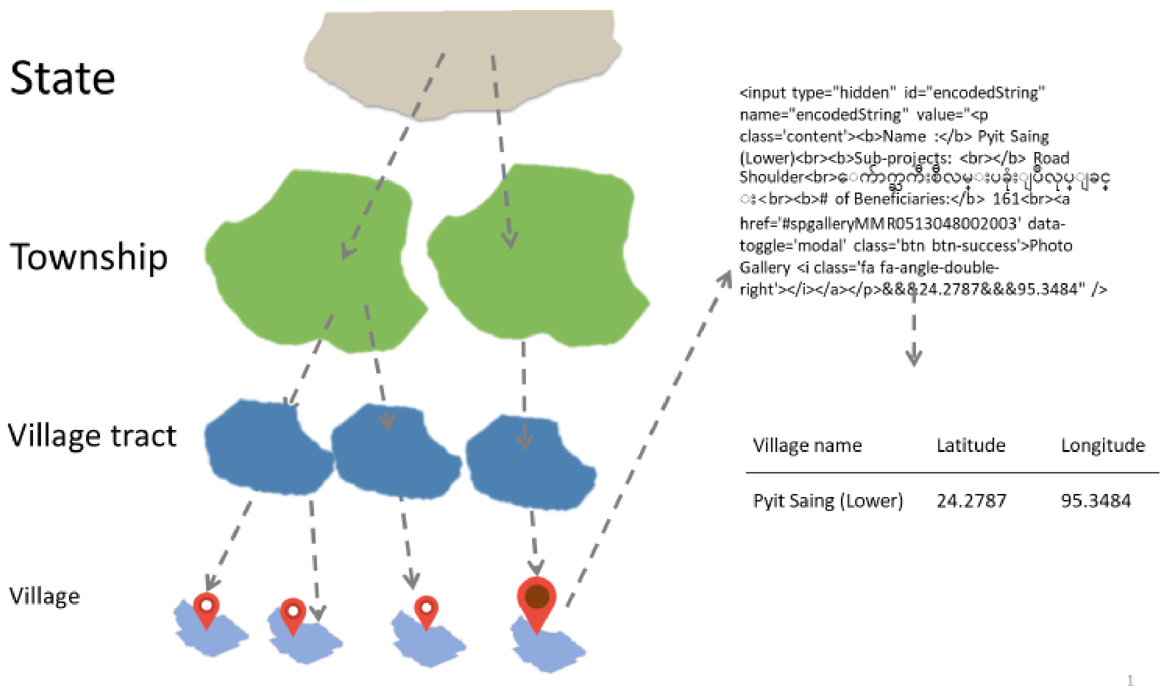

Figure 6. Web scraping process

Wealth and development data

The 2015-2016 Demographic and Health (DHS) Surveys in Myanmar contain asset-based wealth index for 12,500 households. Each household belongs to one of the 442 DHS village clusters or in other words, survey clusters. As latitude and longitude data are only available at the cluster level, I average the wealth index and other development-related measures by 441 geo-coded DHS village clusters.[13] Nightlight imagery is from the 2015-2016 Version 1 Visible Infrared Imaging Radiometer Suite Night Band. From this raster file, I extract radiance values for the locations surrounding the DHS cluster center points and CLD project villages. Armed Conflict Location and Event Data (ACLED) from 2010 to 2019 is also used to measure conflict.

[13] Village cluster ID 437 is missing in the original DHS data set, which makes the total number of clusters 441.

Geographic features

Administrative boundaries of Myanmar are drawn from the country's shapefiles. 1 country-level, 15 state-level, and 286 township-level shape (polygon) files come from the DIVA GIS.[14] In addition to this, (MIMU) provides a source for village-tract and village-level boundaries.

Table 7. Data Sources

	Data	Source
Outcome variable	NCDDP location data	Project management website
	SMU location data	Administrative document, 1st year (2016) performance report by Korea Development Strategies
Poverty and development-related variables	Wealth index and wealth factor score, water, climate, population	2015-2016 Demographic and Health (DHS) Survey by the U.S. Agency for International Development
	Nightlight Version 1 VIIRS Day/Night Band rater data, 2015-2016 (Tile 3: 75N /60E)	National Centers for Environmental Information
	Armed Conflict Location and Event Data (ACLED), 2010-2019	Datasets for Development Economists
	Vulnerability dataset	Myanmar Information and Management Unit
Geographic boundaries	Admin 1 (State) -Admin 3 (Township)	DIVA-GIS
	Admin 4 (Village Tract) -Admin 5 (Village)	Myanmar Information and Management Unit

Main Variables

Main variables for this study are as below and summarized in Table 8.

Outcome variables

The outcome variable in this paper is CLD aid distribution across regions. I use three spatial scales. First, administrative analysis at the township level is advantageous because existing datasets such as vulnerability datasets can be incorporated with this analysis. Second, the DHS village clusters provide actual wealth data. Whereas wealth data in the other two analyses are interpolated values, the second unit of analysis makes it

[14] Recently, the number of the township has increased to 330 according to the Myanmar Information Management Unit (MIMU).

possible to use ground-truth wealth data directly associated with the survey clusters. Last, CLD project village analysis is the most granular level of analysis unique to this study. For each SMU and NCDDP intervention village, I assign location-specific wealth, nightlight, and conflict data based upon the village centroid.

Y1: Aid count per township

The first measure is the sum of aid count falling within a boundary of a township, which is the third administrative unit. [15] Technical assistance for Community-led Development projects is implemented at the township level, and thus the number of CLD projects is counted at the township level. Data that can be used for weighting, such as block grant amount per village is only available in 4,855 villages for year five projects (2017-2018). However, using grant data halves the sample size and can introduce selection bias. A test of the mean difference between villages with and without missing data reveal that villages with grants are more likely to be wealthier, more populous, and take a participatory approach in implementing projects.[16] To examine the entire sample, this study uses aid count as an outcome variable and assumes that each village has one project.

Y2: Aid intensity per village clusters

Second, I develop an aid intensity measure to estimate the number of aid project per unit area. This outcome variable is calculated by weighted aid counts per unit area where the weights are determined by the uniform kernel density estimators with the bandwidth h for cluster i. If d, which is the Euclidian distance between the centroid of the DHS village cluster and the centroid of any project site is less than h (or equivalently that d divided by h is less than one), an aid event is given a weight of 1; if not 0. I conduct analysis at various levels of h from 0.01° (Approximately 1 km), 0.1° (10 km), 1° (100 km), and 2° (200 km). [17]

Formally, for the DHS village centroid (x, y),

$$\hat{f}_h\,(x, y) = \sum_{i=1}^{n} \frac{1}{\pi h} k\,(\frac{d_i}{h})$$

Where h is the radius with center point (x,y), d_i is the distance from village cluster (x, y) to the centroid of all CLD project villages, k is the uniform kernel where $k(d_i/h) = 1$ if $(d_i/h) < 1$; otherwise k=0 , and n is the total number of the DHS village clusters, $1/\pi$ accounting for the circular structure of the area.

Y3: SMU project

Likelihood of being an SMU project is the third outcome variable.

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[15] The third level out of five administrative units from high to low

[16] Evidenced by the number of committee members, % of female members, the number of grievance submitted, % of grievance resolved, and the use of community labor measured by days of labors.

[17] Alternatively, a kernel density estimator can be used with an adaptive bandwidth as Burke et al (2016).

Explanatory variables

Each variable informs different aspects of poverty. Wealth represents asset-based household economic well-being in the long-term. Nighttime remote sensing data are examined with respect to local economic activity. Vulnerability represents non-monetary dimensions of poverty. Water scarcity and rainfall deficit represent sustainable development; conflict represents political development.

Wealth index

The wealth index from the DHS is a composite measure of a household's cumulative living standard, categorizing households into five wealth quintiles, from one (low) to five (high). The wealth factor score is computed as the first principal component of survey responses to questions about ownership of observable assets.[18] The resulting wealth scores are standardized and used to create the breakpoint that defines wealth quintiles. Although the wealth index cannot be used directly to construct benchmark measures of poverty, these asset-based measures are capable of capturing a household's long-term economic welfare in poor regions lacking consumption, expenditure and price data (Sahn & Stifel, 2003; Jean et al, 2015). To make a better inference on wealth distribution across regions, analysis in this paper also explores the fraction of each wealth quintile that lives in each village cluster.

Nightlights luminosity

Satellite images of luminosity at night can be used as a proxy for the intensity of economic production in countries with low-quality statistics systems (Donaldson & Storeygard, 2016). The left subplot of

Figure 7 illustrates that three major cities, Mandalay city, Yangon, and Nay Pyi Taw have the brightest nightlights. Drawn from 2015 and 2016 nighttime raster data, the annual average luminosity values are estimated at the 441 DHS village clusters and 12,282 CLD project villages at various resolutions. I use the resolutions of 5 km by 5 km, 10 km by 10 km, and 2 km for urban and 10 km for rural areas, considering any noise effects present in the data (Bruederle and Hodler, 2017; Doll & Morley 2016). [19] The measurement unit for luminosity is a composite cloud-free radiance value estimated in 15 arc-second (Approximately 463 m) geographic grids with outliers removed and non-lights set to zero.

Vulnerability

A specific measure tailored to humanitarian and development program is the adjusted vulnerability index at the township level. The multidimensional index reflects components of human development alongside the impact of conflict and violence,

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[18] It is first calculated on a household's ownership of selected assets, such as televisions and bicycles, materials used for housing construction, and types of water access and sanitation facilities.

[19] Following Doll & Morley (2016), aggregating up reduces any noise effects present in the data. Some noise is added to the geocoordinates of the center points of DHS clusters by displacing each cluster center point in a random direction and by a random distance of 0-2 km for urban clusters, and 0-5 km for rural clusters, with 1 % of rural clusters displaced by up to 10 km (Bruederle and Hodler, 2017).

through a desk review and analysis of national datasets and information at township level over the period 2014-2016. Aid actors are involved in producing and financing the vulnerability data review. The data is from the MIMU and the Humanitarian Assistance and Resilience Programme Facility (HARP-F), both of which are actively involved in aid.[20]

Conflict

An indicator of needs particularly relevant to fragile states is conflict. The right subplot of

Figure 7 illustrates the number of conflicts and fatalities across the nation. As suggested by the high number of fatalities, the mostly non-Burmese populated border areas have been heavily contested by the Myanmar government, militia, and ethnic armed groups. [21] Spatially, I estimate the minimum and mean Euclidean distance from each CLD village centroid to all the locations of conflict events.

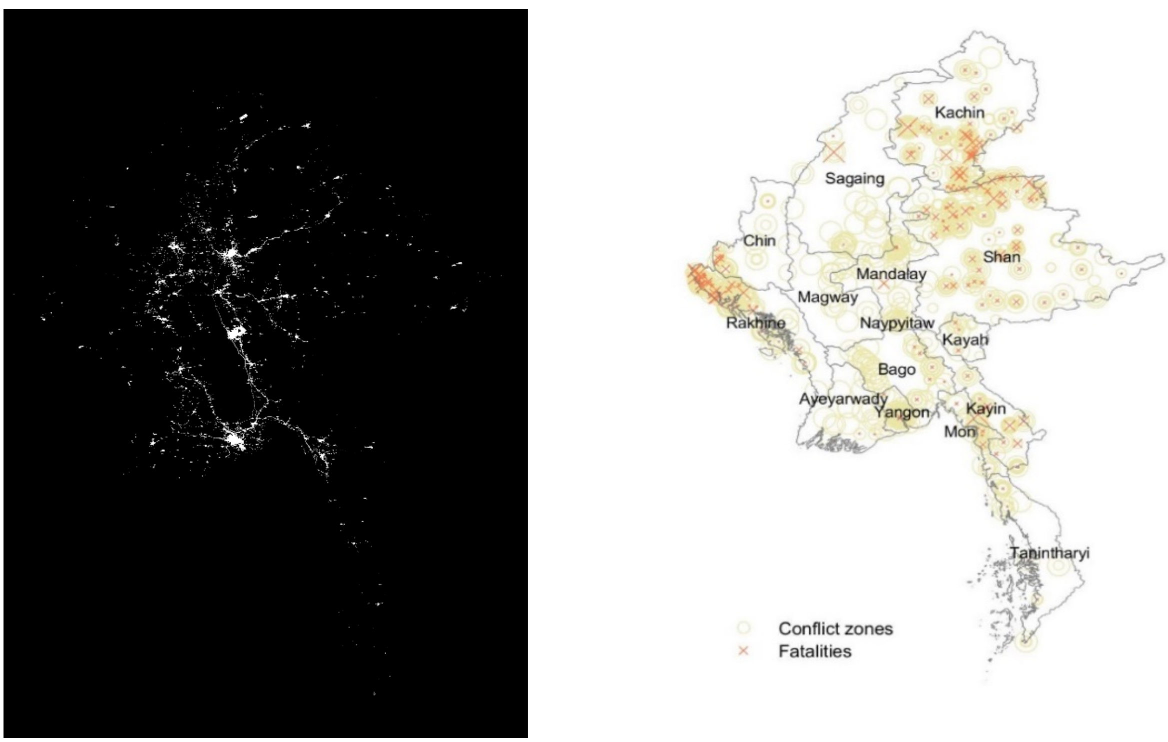

Figure 7. Nighttime Luminosity (left) and Geography of Conflict in Myanmar (right)

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[20] This analysis is financed by the United Kingdom's Department for International Development, the Government of Canada, and European Union humanitarian aid.

[21] They include the Myanmar government and armed forces, state-back militia, and opposition ethnic armed groups (Jolliffee, 2015)

Other development-related variables

Social, political, and sustainable development related variables are also considered. For poor people, access to water is a pre-requisite to achieving a minimum standard of health and to undertake productive agricultural and industrial activities. Variables included are water scarcity measured by the distance to the nearest major water body,[22] and rainfall deficits, which hinder potential vegetative growth. The Global Aridity Index version 2 dataset provides aridity 30 arc-seconds global raster climate data for the 1970-2000 period. Population in 2015 is also included because it is the main variable related to aid volume in cross-country panel studies (Berthélemy and Tichit, 2003; Nunn and Qian, 2014).

Table 8. Variables for Main Analyses

Variable and years	***Y1: Aid count within township***	***Y2: Aid intensity per village clusters***	***Y3: Difference by project village***
Aid 2012-2018	Count of total CLD projects within a township	Weighted count of total CLD aid per unit area	SMU project
Wealth 2015-2016 (Assets)	Interpolated DHS wealth index	-DHS wealth index averaged by cluster -The percentage of the poorest and poor quintile at each cluster	Interpolated DHS wealth index
Nighttime luminosity 2015-2016 (Economic output)		Average radiance	Average radiance
Proximity to water body 2017 (Social development)		- Minimum distance to the nearest major water body,	
Aridity index (Sustainable development) 1970-2000		-The ratio between precipitation and Global Reference Evapotranspiration	
Conflict (Political development) 2010-2019			-Minimum/mean distance to the nearest conflict event
Vulnerability (Multidimensional poverty) 2014-2016	The percentage of the vulnerable in each township		
Population 2015 (Social development)		Population count	

[22] Proximity to water is based on the World Vector Shorelines, CIA World Data Bank II, and Atlas of the Cryosphere. Derived Data Set: A Global Self-consistent, Hierarchical, High-resolution Geography Database, Version 2.3.7. 2017. Aridity is based upon the implementation of a Penman Monteith Evapotranspiration equation for reference crop based on global raster climate data for the 1970-2000 period. Both measures are included in the DHS geo datasets.

Model specifications

This study analyzes the association between poverty measures as explanatory variables and aid projects as an outcome variable in two ways. For the overall research question (Question 1: How much of the variance in CLD projects is explained by poverty?) presence and density analysis are performed. To answer the heterogeneity question (Question 2: To what extent is the targeting of two CDL models different in their orientation toward poverty?), I conducted project analysis, modeling the likelihood of being an SMU project given village poverty status.

Presence Analysis

Presence analysis assesses the probability of any aid project being present in the township as a function of its interpolated wealth index at the township centroid and the vulnerability rate of the township. The distribution of project count has a long right tail and also very high frequencies near 0. Almost 40% of the townships have no aid project, and 60% have less than three projects. Given this skewed distribution with a large number of 0s, logistic regression is suitable. I first use a simple binary logistics relationship between the sum of all CDL projects in a township and the level of wealth and vulnerability in that township. Second, the total area of the township is considered as the control variable for this analysis.

$$log(\frac{p(aid)}{1-p(aid)}) = \alpha + \beta * wealth_i + \gamma * vulnrability_i + \epsilon_i$$

Density analysis

Least squares regression of project occurrence rate per unit area is performed on the poverty, wealth, and development indicators. To conduct meaningful analysis with a continuous outcome variable, having many zero values in the outcome is not desirable. The size of the unit area is therefore set to a bandwidth of *h*=2 degrees. This threshold is larger than village tract unit but smaller than township unit given the average size of the township is about 18 degrees (1,863 km^2), and the average size of village tract is 0.00423 degrees (469 m). For h < = 0.1, there are many non-zero values, and logistic regressions with small bandwidths are conducted to corroborate statistical findings with a large radius.

$$\frac{weighted\ aid\ count}{area} = \alpha + \beta * wealth_i + \gamma * nightlights_i + \delta * population_i$$
$$+ \eta * water_i + \rho * aridity + \epsilon_i$$

Project analysis

The third analysis estimates the magnitude of difference in poverty and conflict between SMU and NCDDP villages. The logit of the probability of being SMU project is fitted to the predictors: the wealth index, nightlights, and conflict.

$$log\left(\frac{p(SMU)}{1-p(SMU)}\right) = \alpha + \beta * wealth_i + \gamma * nightlights_i + \delta * conflict_i + \epsilon_i$$

Results

Descriptive analysis

The mean and standard deviation of variables

Table 9 reports the means and standard deviation of variables. Project villages are composed of 20% of the total 63,938 villages. Among total 286 townships, 40% (117 townships) have no project, and 20 % have a project between one and three. The mean of CLD project count is 43 per township with very high variance (93) and left skewness; the median of the value is only one project per township.[23] The average share of vulnerable population per township is more than a half (60%).

Within 0.1° (10 km), 1° (100 km), and 2° (200 km) radius of a DHS survey village cluster, there is about 0.06, 300, and 3500 aid projects per area respectively. Aid density variables are not strictly normally distributed. Aid count falling within a radius of 2° is symmetric (skewness 0.0018) and lightly right-tailed (Kurtosis 1.850) whereas density with a radius of 1° is not symmetric with many zeros but have small outliers (Kurtosis 0.0374). The mean distance between a village cluster to all aid sites is approximately 40 km: 3.90 digress for all village clusters (43.5km) and 4.04 degrees (448 km) for the poorest villages in the lowest wealth quintile.

The average nightlight radiance value of project villages is 0.09, lower than the DHS village cluster average of 1.31 (normalized z score of -0.34 lower). The mean interpolated wealth index for project villages is also 2.54, moderately lower than the mean of 3 for DHS village clusters (normalized z score of -0.39). Villages are on average approximately 5 degrees (500 km) away from all conflict events. The distance to the nearest conflict event is only 0.02 degrees away.

[23] The distribution of the project is highly skewed to the left (skewness 3.11 and Kurtosis 14).The standard normal distribution has a skewness and a Kurtosis coefficient of zero.

Table 9. The mean and standard deviation of main variables

Analysis	Variable	Observation	Mean	Std. Dev.	Min	Max
Y1 count (township)	aid count	286	42.91	92.71	0	614.00
	vulnerable population (%)	272	59.97	9.32	28.29	86.44
	vulnerable population	272	92,629	52,535	1,131	373,960
	Area (km^2)	286	2343	1919	101	12311
Y2 density (village cluster)	aid count within 1 km	441	0.0000113	0.0000495	0	0.000828
	aid count within 10 km	441	0.06	0.10	0	0.79
	aid count within 100 km	441	280	198	0	962
	aid count within 200 km	441	3,469	1,950	76	7,186
	distance to all aid sites (°)	441	0.39	1.01	8.76	2.97
	wealth index	441	2.94	1.02	1.10	5.00
	wealth factor score/10,000	441	0.05	7.63	-14	24
	The share of 1st, 2nd wealth quintile of the cluster (%)	441	0.004	0.003	0	0.018
	nightlights 2015	441	1.31	3.62	0	25
	nightlights 2016 (10*10 km)	441	1.31	3.68	0	29
	nightlights 2016 (5*5km)	441	1.44	3.91	0	24
	population 2015	441	66,347	155,889	79.10	2,458,837
	log of population 2015	441	10.31	1.33	4.37	14.72
	population density 2015	441	1,138	3,089	1.70	25,152
	aridity	441	14,926	8,921	3,500	37,371
	proximity to borders (m)	441	81,833	77,403	9.53	287,064
	proximity to the water (m)	441	141,642	87,112	0	481,324
Y3 project (village)	wealth index (linear)	12,282	2.53	0.66	0.38	5.31
	NCDDP	12,182	2.52	0.65	.38	5.31
	SMU	100	3.29	0.86	1.67	4.80
	wealth index (nearest neighbor)	12,282	2.54	0.86	1.10	5
	NCDDP	12,182	2.53	0.85	1.10	5
	SMU	100	3.46	1.00	1.46	5
	nightlights 2016 (10*10 km)	12,282	0.09	0.52	0	19.32

NCDDP	12,182	0.07	.432	0	19.31
SMU	100	1.91	2.56	0	9.89
nightlights 2016 (5*5 km)	12,282	0.09	0.52	0	22.36
NCDDP	12,182	0.07	0.48	0	22.35
SMU	100	2.28	3.15	0	11.76
mean distance to conflict	12,280	4.95	1.40	2.70	11.36
NCDDP	12,182	4.95	1.40	2.70	11.36
SMU	100	4.56	1.39	2.77	8.63
min distance to conflict (°)	12,282	0.21	0.14	0.00	0.94
NCDDP	12,182	0.21	1.14	0.0001	0.94
SMU	100	0.09	0.12	0.0022	0.50

Aid Distribution

The locations of CLD projects within the State[24] and township boundaries are illustrated in the left subplot in Figure 8. The figure shows that CDL projects are taking place at the national level in all states but not in all townships. The yellow circle denotes DHS village clusters where geo-coded wealth indices are available. As DHS village cluster locations and aid project sites do not always correspond to each other, many villages participating in CLD projects do not have wealth data corresponding to their locations. The inconsistency between the DHS survey clusters and aid sites appear to be larger in some states such as Shan State and Magway than others. Although this map gives a snapshot of aid allocation across the nation, given the national scale of CLD projects, it is useful to create a map that distinguishes clustered aid spots from sparse aid spots.

The right subplot highlights aid "hotspots." The map visualizes the weighted aid count where weights are determined by the distance from a DHS village cluster to all aid sites using uniform kernel density estimators.[25] Aid projects are clustered in the center, particularly in Nay Pyi Taw (the capital city), Northwestern parts of Kayah, and Ayewarwady. Clusters of aid hotspots are also found in the main cities in central regions including Yangon (capital until 2006, the largest city and commercial center), Mandalay (the second largest city, and the last royal capital), and Kayin. In contrast to these densest hot spots, aid is sparse in the State of Shan, Kachin, Tanintharyi, Sagaing, and Rachine.

[24] Region, Self-administered Zones and Division

[25] If any aid events occur within the radius of h, those aid events were counted as 1, adjusted for the area, λ, and assigned as an aid spot. The size of the bubble in the subplot on the right is calculated by setting h =0.1° (approximately 10 km) and multiplying λ_i by 100.

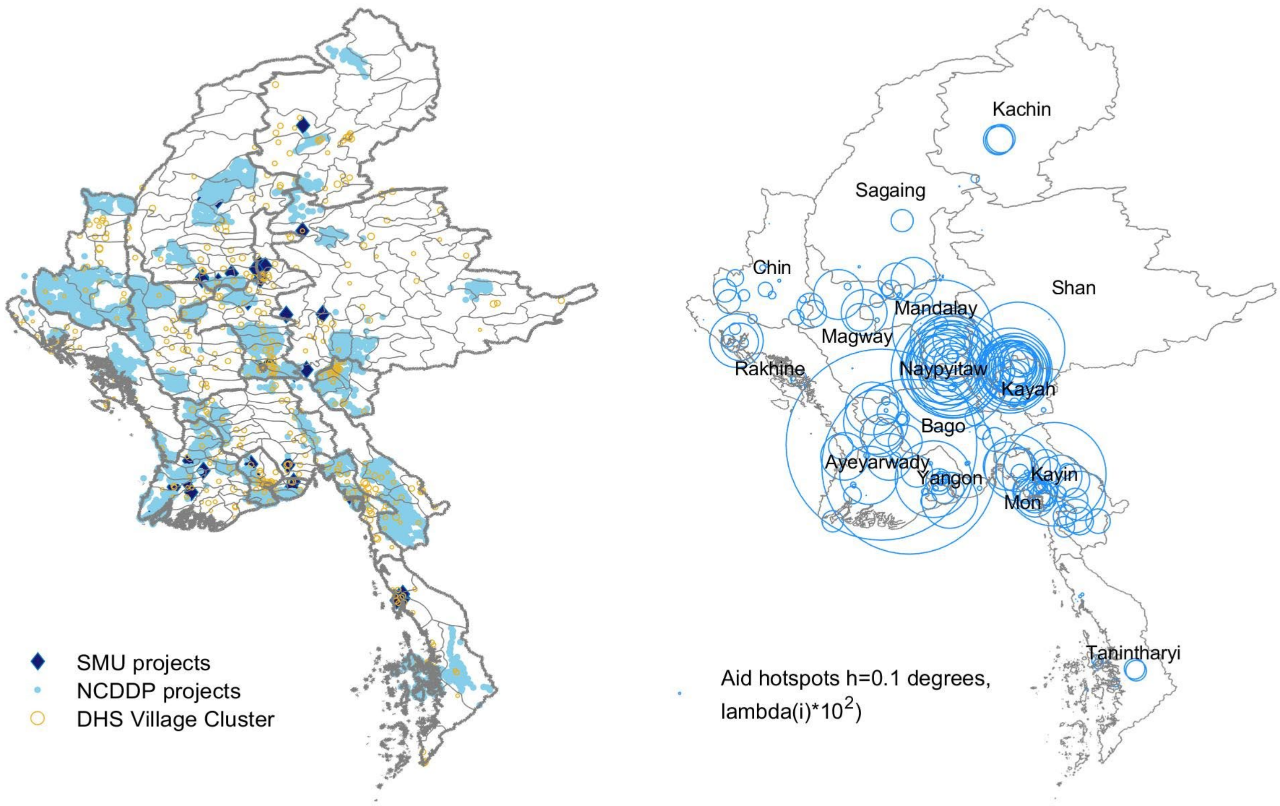


Figure 8. Distribution of Aid

Wealth and Aid

Regional profiles of wealth and aid by the largest administrative unit, States and Regions, are summarized in Table 10 Wealth and Aid by State. Out of 15 States and Regions, Rakine has the highest share of the population in the poorest quintile and highest rates of vulnerability and has the lowest population in the richest quintile. However, Rakine is only ranked in the 9th place when it comes to the number of aid projects received. Rakine's Gini coefficient is second largest (0.35) to Nay Payi Taw (0.38), which is the wealthiest state with the highest fraction of population in the wealthiest quintile and the lowest in the poorest quintile (6%). Nevertheless, these two states have the highest Gini coefficients, i.e., most unequal income distributions of the fifteen states. There is also an urban and rural divide. A majority of households (72%) live in rural areas, but more than half of the rural population (51%) belongs to the bottom fifth and fourth quintile compared with only 9% of the urban population.

Table 10 Wealth and Aid by State

Region & State	Aid count	Vulnerable population (%)	Area	Percent distribution of the population by wealth quintiles, DHS 2015-2016					Gini coefficient
				lowest	second	middle	fourth	highest	
Ayeyarwady	**89.56**	58.71	1254.54	**41.80**	**24.60**	15.80	11.40	6.40	**0.32**
Bago	34.50	55.03	1377.57	18.90	**23.60**	23.40	20.10	14.00	0.30
Chin	**82.56**	62.13	4118.71	21.30	**29.40**	**27.60**	13.70	8.00	0.29
Kachin	15.17	65.74	**4929.05**	13.20	23.00	22.00	**25.10**	16.70	0.29
Kayah	78.50	55.66	1944.14	11.30	21.30	25.20	**26.50**	15.70	0.26
Kayin	**143.14**	**70.10**	**4276.87**	24.30	18.50	17.10	21.50	18.50	0.31
Magway	32.36	56.23	1766.87	18.50	23.40	**27.40**	18.40	12.30	0.24
Mandalay	61.65	52.23	1402.89	6.90	17.80	23.30	24.30	**27.70**	0.23
Mon	45.50	54.96	1154.39	20.20	15.70	21.00	21.20	21.90	0.30
Nay Pyi Taw	7.00	42.49	138.54	22.80	20.70	19.40	16.30	20.70	**0.38**
Rakhine	33.44	**71.67**	2230.25	**52.80**	21.80	12.90	8.20	4.20	**0.35**
Sagaing	26.72	57.65	2457.62	8.00	22.40	28.00	**27.90**	13.70	0.20
Shan	19.87	**68.50**	2993.72	18.50	20.40	15.20	20.80	**25.00**	0.28
Tanintharyi	36.78	59.73	**4584.61**	**24.90**	22.30	17.80	20.60	14.40	0.32
Yangon	44.85	51.64	735.95	6.00	9.10	14.90	23.10	**46.90**	0.22
Average	50.11	58.83	2357.71	20.63	20.93	20.73	19.94	17.74	0.29

<Note: The top three states and regions for each column are in bold, Source for Gini Coefficient and Wealth quintile: Myanmar Demographic and Health Survey Final Report 2015-2016>

While this traditional method of disaggregating poverty by States gives a glimpse of the need-intervention match, it does not tell how aid has been distributed to the main unit of CLD intervention ― to a small community. Nonetheless, disaggregating information by the village level would add noise to the analysis for many reasons. Data are often not available at that level, and the unique identifying information such as names or administrative boundaries at small administrative units are not always consistent or clear.

Finding the middle ground, I visualize poverty and aid at a much granular resolution that does not hinge on administrative boundaries. In Figure 9, gridded wealth fields at a high resolution of 0.1° by 0.1 ° are overlaid onto project locations in two subplots. The top plot depicts aid distribution over wealth fields; the 3-dimensional plot on the bottom projects wealth on the Z-axis where height indicates the degree of wealth. NCDD projects in light circles are located in various wealth fields while some SMU projects in dark diamond shapes are at the top of the wealth index.

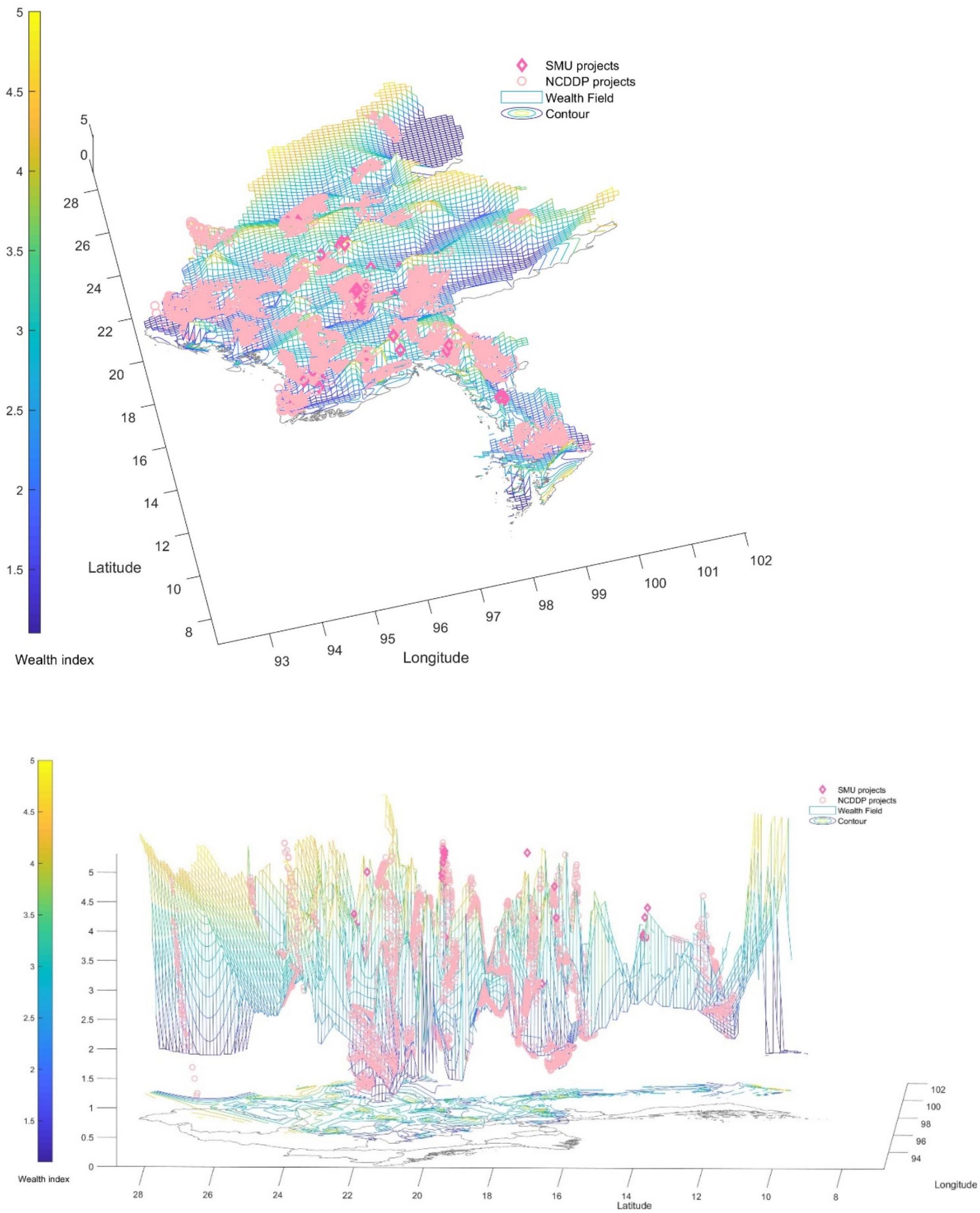


Figure 9. Project Sites Overlaid on the 3-dimensional Wealth Field

Relationship between wealth, nightlights, and other measures

This study relates aid with various indicators of poverty including wealth and nightlights. I check the potentials for multicollinearity among predicting variables. The interpolated wealth index is only moderately correlated with the percentage of vulnerable populations (Pearson *r* correlation coefficient (P) and Spearman ρ rank correlation (S) =-0.20). The wealth index is correlated with nightlights (r=0.46, S =0.66). The fact that wealth quintile is negatively correlated with the share of the poor and poorest quintiles of the region (P=-0.88, S=-0.95) supports the use of wealth index as a proxy poverty measure. Wealth is also negatively related to being in rural areas (P=-0.73, S= -0.69).

To examine the relationship between nightlights and wealth from a different angle, I train nightlight imagery to predict wealth. I divide the DHS dataset into a training (80%) and test data set (20%) and fit a ridge regression model of cluster-averaged wealth on a nightlight using 10-fold cross-validation approach. For held-out data sets, nightlights accurately predict wealth 18% of the time; some of the best models are corrected 24% of the time.

When fitting a simple regression model of wealth as a function of nightlights, nightlights explain approximately 22% of the variance in wealth factor score (Left subplot of Figure 10).[26] In developing countries, luminosity levels are generally clustered near or little above zero with little variations, and the measure exhibits strong positive skewness. Myanmar's R^2 is considerably lower than R^2 of other developing countries such as Rwanda (0.74) on the right subplot of the Figure below. It is also lower than Haiti (0.31) and another South Asian country, Nepal (0.37).

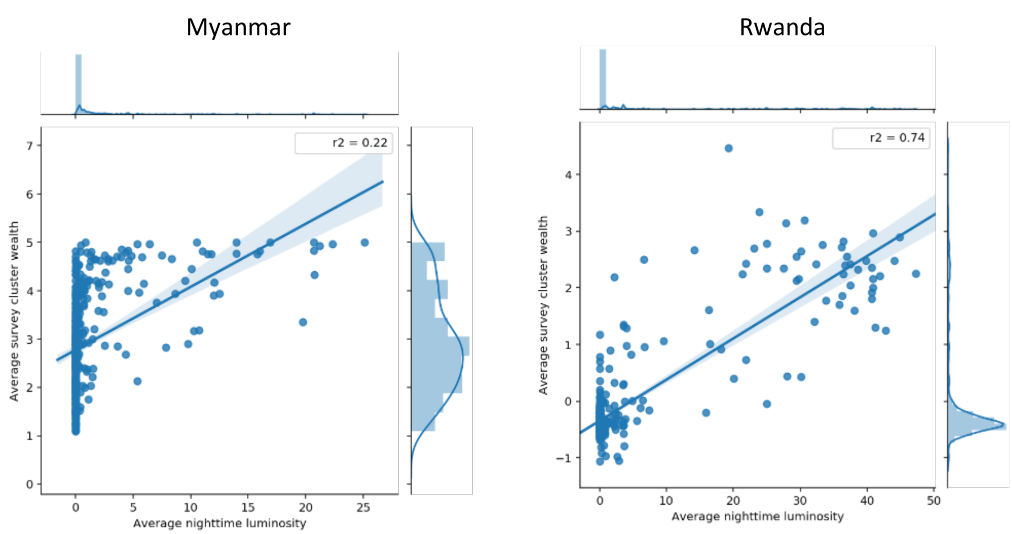


Figure 10. Correlations between the Wealth Index and Nightlights Intensity

[26] R-squared is high when using wealth factor score (0.21 vs 0.26 for a 10 by 10-pixel resolution) than wealth index (0.26 vs 0.28 for a 5 by 5 resolution). The r-squared also changes slightly by resolution. Nightlights measures using a lower, 10 by 10 pixels resolution, has lower R-squared (26%) than a higher, 5 by 5-pixel resolution. However, nightlight measured in 2015 and 2016 are very similar (*r*= 0.97).

Nighttime luminosity also corresponds to higher population density (P=0.89, S=0.76) but negatively correlated with residency in rural areas (P=-0.44, S=-0.61). [See correlation matrices in Appendix J. Correlation among Wealth-Related Measures].

NCDDP dominates overall tendency of CLD given that NCDDP is almost 100 times larger than SMU. Separating two models show differences in targeting. On average, SMU villages are wealthier and brighter but closer to conflict areas. As the first histograms in Figure 11 illustrate, average wealth index of SMU project villages (3.29) are 0.77 higher than that of the NCDDP project sites (2.52), using linear interpolation. The second histogram shows that the mean distance to all conflict events is 0.39 degrees shorter for SMU (4.56) than NCDDP (4.95).

Two aid models also differ by nightlight. As seen in the third histogram, both projects are mostly taking places in villages with dim lights. The distributional difference is more apparent for non-zero values. Cumulatively, 95% of the NCDDP projects and 51% of the SMU projects are taking place in villages whose radiance value is under 0.34.[27] Above this radiance value, 99% of the NCDDP are taking place under 1.21 radiance value while SMU shows a broader wider spectrum percentage wide.

[27] The share of the projects at zero radiance value is the largest, which makes up of approximately 0% of NCDDP and 30% of SMU.

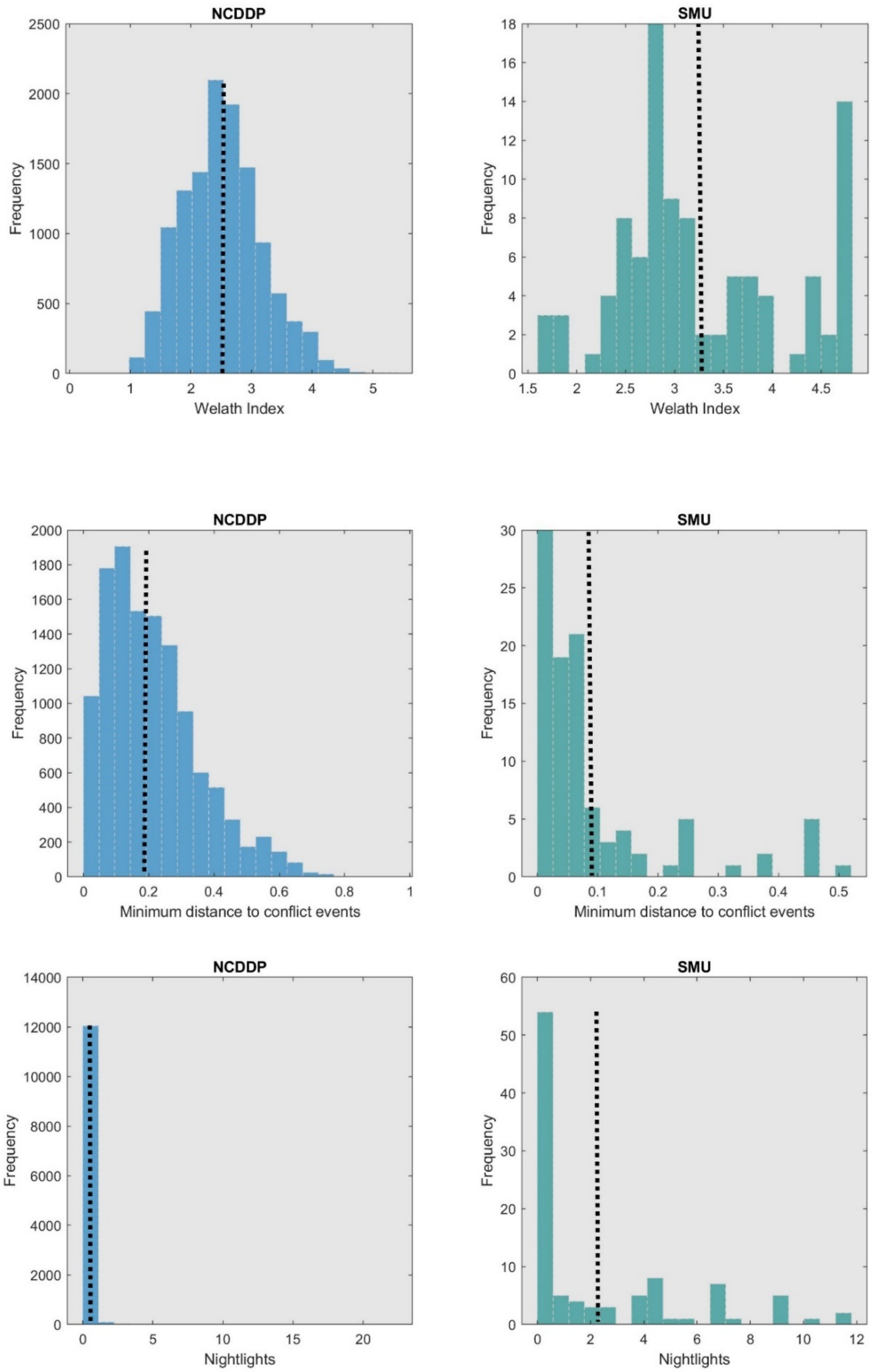


Figure 11. Distribution of Wealth, Nightlights, Min Distance to Conflict by Aid Models

Statistical Analysis

Association between Wealth and Project Location

Presence Analysis

As each increment of a vulnerable population rises, the likelihood of aid presence in that community declines. The results are presented in Table 11. In Column 4, the odds ratio of being a project township is reduced by a factor of 0.997 (0.3%) for each percentage point increase in the share of vulnerable population. This result is consistent in Column 2-4 regardless of adding more control variables. Controlling for wealth index slightly increases the significance of the vulnerability as a predictor but does not statistically increase a model fit measured by the likelihood ratio of model 2 to model 3 (Chi-square 0.64, df=1).

Unlike vulnerability, the wealth index is negatively correlated with the odds of receiving CLD aid but not statistically significant. The relationship between wealth and aid presence is explored with or without controlling for vulnerability and the size of the area. Area variable accounts for the fact that the optimal number of aid projects may increase with the area of a region (Brigg et al, 2015).[28] In all Columns in Table 11, wealth has insignificant predictive power in explaining variation in aid presence per township. The full model in the right-hand column explains only 3% of the variability in aid presence.

[28] For example, all else equal, longer roads or large bridges are needed in larger regions.

Table 11. Results of Presence Analysis

	(1)	(2)	(3)	(4)
Aid Count	Wealth	Vulnerability	Wealth & Vulnerability	All
wealth index	-0.00339 (0.116) OR=0.997		-0.107 (0.135) OR=0.899	-0.104 (0.135) OR=0.901
vulnerable population (%)		-0.0447** (0.0139) OR=0.956	-0.0472*** (0.0143) OR=0.954	-0.0493** (0.0155) OR=0.952
area				0.0000266 (0.0000719) OR=1.000
constant	0.377 (0.331) OR=1.4576	3.131*** (0.852) OR=22.890	3.563*** (1.016) OR=35.253	3.620*** (1.030) OR=37.350
pseudo R^2	0	0.0298	0.0316	0.0319
Number of Observations (Townships)	286	272	272	272

<Note: * p<0.05, ** p<0.01, *** p<0.001, Standard errors in parentheses, OR=Odds Ratios>

Density Analysis

Similar to the presence analysis, Ordinary Least Squares (OLS) estimates report somewhat mixed results regarding the direction of poverty-related variables [Table 12]. Nightlights are a strong and consistent predictor of aid intensity across all models whether models include (Column 9-11) or exclude wealth (Column 5-8). In Column 8, one unit increase in the composite radiance value changes the number of projects by 86 within a radius of 2 degrees of a DHS village cluster, holding other variables constant. This nightlight model excluding wealth explains about 37% of the variation in the aid density across areas surrounding village clusters.

However, there is still evidence that need-based allocation is in place. The wealth variable becomes significant when holding control of nightlights intensity (Column 9-Column 11). It indicates that when nightlights and water access variables are equal, aid goes to less wealthy villages at a p-value of 0.01. The main model in Column 9 suggests that one score increase in the wealth index is related to a reduction of aid density by 227. In contrast to nightlights, wealth is not a strong predictor by itself. Wealth models that exclude nightlights are insignificant and inconsistent. (Column 1-4).

Concerning covariates, more aid also flows to areas with a larger population, farther from the major water body, and areas with a rainfall deficit for potential vegetative growth. A 1% increase in population would yield an increase of approximately 3 projects per area. A 1 km increase in the distance between village cluster to the nearest water body is associated with 8 more aid projects. F-statistics indicate that the model fit of Column 9 is statistically better than Column 8 without wealth (F=7.34, P=0.007). Column 10 indicates that a log transformation of nightlights after replacing 0 with 0.01 yields slightly better adjusted R-squared.[29] An interaction term between wealth and nightlights dummy variable is negative but not significant in Column 11. Models with all the variables including wealth explain about 38-39% of the variation in the weighted aid counts within the vicinity of DHS village clusters.

I explore whether aid distribution differs by extremely poor villages with no lights as compared to villages with some lights by dividing the sample into two subsets for comparison. The results indicate that pro-poor targeting is stronger among villages that are not extremely poor [Appendix L]. Regarding villages with an annual average of zero radiance value, wealth is not statistically significant in any models regardless of control variables. The same for population. Only water and aridity variables are significant. For a subset of villages with more than zero nightlights, the effect of wealth on the reduction of aid count is stronger with a coefficient of -367.9 (140 lower than the entire data set) with a p-value of 0.001, controlling for all other variables including nightlights. However, wealth is still not significant without controlling for nightlights.

[29] To meet the assumptions of linear regression, a number of strategies are adopted. They include log transformations of skewed variables, outlier removal, and checking for multicollinearity. The log transformation of population and nightlights variables correct skewness of the variables. Three outlier clusters with high residual values and leverages are removed (cluster 74, 270, and 326) to reduce the undue influence of individual observations on the coefficients. Adjusted R^2 increase to 0.382 and other coefficients remain similar. To avoid multicollinearity, I check for variance influence factor and highly correlated variables (more than 0.70 Pearson *r* correlation coefficient with one another) are not combined in the model. They are population density and nightlights; the share of the 4th and 5th quintiles and wealth; and proximity to national borders and aridity. The rural variable is dropped because it is binary and not significantly enhance the model fit. Homoscedasticity of residuals assumption is weakly satisfied. There are some patterns to the residuals plotted against the fitted values.

Table 12. Analysis of Aid Density

Aid Density within 2° radius	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
wealth index	64.4 (90.94)	74.60 (0.88)	-31.88 (-0.41)	-21.38 (74.45)		108.6*** (4.41)			-227.5** (83.98)	-444.1*** (105.60)	-365.7** (133.20)
nightlights 2015					156.4*** (24.61)		120.9*** (5.69)	86.37*** (21.38)	119.9*** (24.57)		
log of population		527.4*** (8.06)		403.6*** (57.51)		438.7*** (6.54)		336.7*** (58.86)	307.1*** (59.45)	210.2** (65.93)	222.3** (67.11)
proximity to the water body			-0.0093*** (-10.34)	-0.0082*** (0.000877)			-0.0089*** (-10.15)	-0.0080*** (0.000862)	-0.0080*** (0.00)	-0.0078*** (0.00)	-0.0077*** (0.00)
aridity			-0.0683*** (-7.58)	-0.0082*** (0.00855)			-0.0632*** (-7.37)	-0.0626*** (0.00829)	-0.0662*** (0.01)	-0.0608*** (0.01)	-0.0614*** (0.01)
log of nightlight (2015)										214.0*** (39.07)	233.8*** (44.14)
wealth × nightlights											-99.15 (102.80)
constant	3280.5*** (282.90)	-2188.2** (-3.01)	5912.3*** (18.50)	1519.0* (695.7)	3265.2*** (94.62)	-1196.9 (-1.74)	5519.9*** (28.07)	1965.8** (649.7)	2935.9*** (737.80)	5275.3*** (961.30)	5233.5*** (962.30)
Observations	441	441	441	441	441	441	441	441	441	441	441
Adjusted R-squared	-0.001	0.126	0.279	0.350	0.082	0.162	0.328	0.374	0.383	0.391	0.391

<Notes: * p<0.05, ** p<0.01, *** p<0.001, Standard errors in parentheses, Nightlight used here is 2015 because it yields a better model fit than nightlights 2016.>

Comparison of Two Aid Models

The two aid models have distinctive targeting practices. NCDDP is targeted towards villages with lower assets and lower luminosity, and SMU is targeted towards villages whose distance to the nearest conflict events is closer. The significance of these effects and their directions are consistent across all of the models presented in

Table 13. The full model with all variables (Column 7) indicates that for each point increase in the wealth index, the odds of being a SMU treatment village increase by a factor of 2.37, holding other variables constant (p-value of 0.01). Similarly, a one radiance value increase in nightlight intensity is associated with a 44.5% increase in the odds of receiving SMU aid. [30] In contrast, a one degree (approximately 100 km) increase in the distance to the nearest conflict event reduces the odds of being a SMU site from 1 to 0.0016.

Wealth, luminosity, and conflict together account for one-fifth of the variation in whether or not a village is SMU as opposed to NCDDP. The model in Column 7 fits the data best indicated by statistically significantly higher maximum log likelihood ratio (-455.07) than a more parsimonious model in Column 6. The difference between the nested model in Column 6 and full model in Column 7 is significant with likelihood ratio statistics of Chi 32.68 (df=1) with a p-value lower than 0.001. It is also noted that the combination of nightlights and conflict in Column 6 has better explanatory power than the combination of wealth and nightlights in Column 4 or wealth and conflict in Column 5.

This result is consistent with the targeting strategies of the two projects: SMU aims towards economic development of accessible townships as model cases, and the NCDDP aims towards poverty reduction for remote villages. The analysis also finds the NCDDP avoids conflict areas.

[30] $\{(e^{(0.368)} - e^{(0)})/ e^{(0)})\}*100$ or $\{(1.445-1)/1\}*100$

Table 13. Comparison of the SMU and the NCDDP

SMU	(1)	(2)	(3)	(4)	(5)	(6)	(7)
interpolated wealth	1.521*** (0.137) OR=4.577			0.984*** (0.150) OR=2.674	1.279*** (0.139) OR=3.592		0.861*** (0.151) OR= 2.365
mean nightlights 2015		0.620*** (0.0442) OR=1.859		0.464*** (0.0484) OR=1.590		0.491*** (0.0452) OR=1.634	0.368*** (0.0490) OR=1.445
minimum distance to conflict			-11.258*** (1.416) OR=0.0001		-9.081*** (1.379) OR=0.0001	-7.255*** (1.311) OR=0.0007	-6.409*** (1.3033) 0.0016 OR= 0.0016
Constant	-9.198*** (0.458) OR= .0001	-5.113*** (0.115) OR= 0.0060	-3.242*** (0.166) OR= 0.0390	-7.818*** (0.463) OR=0.0004	-7.197*** (0.512) OR=.00074	-3.979*** (0.194) OR=0.0187	-6.463*** (0.510) OR= 0.0015
Observations	12282	12282	12282	12282	12282	12282	12282
Pseudo R-squared	0.1038	0.1512	0.088	0.1873	0.1643	0.1881	0.2163
Log Likelihood	-520.40	-492.84	-529.55	-471.92	-485.28	-471.42	-455.07

<Note: * p<0.05, ** p<0.01, *** p<0.001, Standard errors in parentheses, OR= Odds Ratios>

Robustness Check

I check model performance in several ways. First, I rerun the main density analysis in Column 9 and 10 in Table 12 using ridge regression. Given the concerns on multicollinearity and high directionality, ridge regression adds a degree of bias to the regression estimates to reduce variance and guards against overfitting. The ten-fold cross-validated ridge regression of the models in Column 9 and 10 gives R-squared of 0.319 and 0.316 as compared to the OLS estimates of 0.375 and 0.379 respectively. When adding all the possible variables including being rural areas and proximity to national borders, the R-squared goes down to 0.314 as ridge regression penalize the size of parameter estimates. Thus, the variation explained by the main specification is slightly reduced but remains similar.

I also vary the radius of aid density. First, aid density is examined with a radius of 0.1 degrees (10 km) considering that it may be less accurate to apply the same wealth index to large areas. In this case, higher wealth was significantly related to low aid count. One score increase in wealth index is associated with -0.17 decrease in aid count with a p-value of 0.01, holding everything else constant. Nightlight intensity was still positive, indicating that one unit increase in nightlight is associated with 0.006 reductions of aid count (p-value 0.01). Aridity was also still negative, but its magnitude is negligible. This model explains about 3% of the variation in the weighted aid count. When using the smallest radius such as 1 km, the significance of wealth index becomes larger but at the cost of small magnitude and small R^2. Most of the village clusters have either 0 aid or less than 0.000828 counts of aid.

As nightlights are one of the main explanatory variables, I also vary measures of luminosity. I change years of the satellite imagery (2015 vs. 2016), resolutions (high: 5km by 5 km; low: 10km by 10km; or mix: 10 km by 10 km for rural areas and 2 km by 2km for urban areas), transformation and imputation methods (no transformation vs. log transformation with or without replacing 0 with 0.01 before transformation). In all estimations, nightlights are strong and significant predictors. The coefficient of nightlights ranges from 91 -236 [Appendix K]. While the base model of nightlights 2016 with a fine resolution has the lowest coefficients, the log of 2015 nightlights using mixed resolution without replacing 0 before log transformation has the highest coefficients. The R squared of the latter model better fits the data, explaining about 40% of the weighted aid count as compared to 37% of the base model.

Lastly, I check calibration by comparing different measures of project analysis. I change interpolation methods for wealth (linear interpolation vs nearest neighborhood interpolation), aggregation methods for distance to conflict (distance to the nearest conflict event vs mean distance to all conflict events), as well as measurement for nightlights (mean vs median and high vs low resolution). Overall the estimation remains similar and consistent. One exception is that when using mean distance to all conflict events. Conflict variable becomes insignificant when accounting for other covariates. Among various nightlights measures, high-resolution nightlights aggregated by median value over village clusters, using the nearest interpolation method gives the most robust coefficients for all parameters used.

Conclusions

This study analyzes the association of poverty and aid in Myanmar by measuring aid to villages across a range of spatial scale from large to small and with or without administrative boundaries. It starts with a small administrative unit and then moves onto village clusters where ground truth wealth data exist. Lastly, it examines measures of wealth and development surrounding aid project villages. This study does not describe a the causal effect of aid distribution but show how aid allocation is aligned with needs based on different aggregation methods across space.

CLD aid shows mixed evidence in needs-based targeting. CLD in Myanmar disproportionately flows to better-off communities, as indicated by a lower share of vulnerable populations per township and densely aided areas that shine brighter. However, unlike previous literature that argues state-level aid favors the richest, this study suggests that a need-based allocation is also in place in Myanmar at least for CLD, an aid instrument known for its emphasis on participation and inclusion. Within villages of similar levels of population and electrification, aid goes to areas with low assets. More aid also goes to village clusters with less access to water and with rainfall deficits.

Another finding is that the two aid models target differently as hypothesized. NCDDP goes to less wealthy villages with darker nightlights indicating its poverty-orientation. On the other hand, SMU goes to areas in close proximity to conflict zones. This finding is aligned with how the two donor organizations conceptualize social capital. The NCDDP model perceives social capital as inclusion and collaboration, whereas social capital from SMU includes competition that incentivizes performance and resource mobilization.

Findings in this study suggest that nuances captured in nightlight luminosity can predict CLD aid density in Myanmar. Brighter nightlights are strongly correlated with higher aid density in that community. It is also a robust predictor of being a SMU project village. The model fit of this variable is better than other poverty-related variables. Earlier studies identify some limitations of using nightlights in distinguishing different levels of economic activity in impoverished communities that are uniformly dark. Given the national scale of CLD, aid projects are occurring at a wide spectrum of regions with different income and consumption level. Therefore, nightlight shows promise in capturing the variability of economic development in target villages and improving prediction of aid allocation.

This study has limitations given that the results have some inconsistency depending on the measurements and the units of spatial analysis. It is unexpected that the asset-based measures and other variables such as nightlights and vulnerability are inversely related. The results are to some degree sensitive to the bandwidth adopted. When exploiting aid density in a minimal bandwidth, less wealthy villages clearly receive more aid. In the future, units of interpolation and aggregation can be simulated using adaptive bandwidths (Burke et al. 2011).

This study also does not evaluate which measures are more reliable. The accuracy of different poverty measure can also be compared and evaluated. For instance, multi-spectra daytime satellite imagery, single-band nightlight data, and geospatial interpolation such as kriging,[31] can be trained to predict wealth using the DHS and the best performing measures can be used to study aid distribution (working paper). The results of this study are in line with the author's work in progress that uses daytime satellite imagery to measure poverty and predict CLD aid per capita in Myanmar.

This study suggests a few avenues for future research. When more data about the investment amount of CLD for 2017-2018 and 2018-2019 become available, future research can use block grant per capita per village as an outcome variable instead of the total number of aid projects, which consider all projects to be equal in terms of their value. Furthermore, observing dynamic changes of targeting is another area of study with the newly released year six data set. The year six data set is a subset of the year five data set, and future study can explore the factors affecting selection into the year six project cycle. Following the first free elections in 25 years, held in November 2015, Myanmar underwent a transfer of power from the military-led regime to

[31] Kriging method accounts for spatial auto correlation between wealth and nightlights.

a democratic-authoritarian hybrid.[32] Whether this regime change has affected aid targeting can be a potential impact evaluation study. More qualitative inputs can also improve the models to explain aid distribution. They include an in-depth review of donors' village selection criteria and processes, validation of measurement for difficult-to-quantify selection criteria (e.g., existing capacity of villages), and analysis of latent factors. Outlier villages can also be further examined through qualitative lenses. For instance, village clusters such as 74, 270, and 326 (Please see wealth and development data under the Methods section) deviate from the general patterns with high residuals and leverages.

This study promotes evidence-based targeting for area-based interventions, lacking location specific and timely data. It addresses the disconnect between communities wanting to mobilize resources and development agencies identifying populations to serve. Nightlight data are globally consistent, and DHS surveys are available for over 90 countries. A similar analysis can be conducted to link CLD distribution with poverty in other fragile states such as Afghanistan, Sierra Leone, Indonesia, the Philippines, and Nepal. Exploring new data sources and synthesizing them with administrative and survey data at a fine-grained level extends their utility as a policy design and evaluation tool.

[32] Myanmar was classified as "hybrid regime" in 2016 by the Economist Intelligence Unit's Democracy Index.

CONCLUSION

This dissertation draws attention to alternative forms of evidence to target, design, and evaluate international aid in the Global South. The first chapter commences with poverty assessments at the global level. The discrepancy between poverty measures highlights the pronounced dimensions of poverty across developing nations. Pakistan, Ethiopia, Cambodia, Nepal Angola, and South Africa experience capability poverty while Uzbekistan, Zimbabwe, Lesotho, Syria, DR Congo, and the Gambia experience income poverty. There are 1.5 times more capability poor countries than income poor and the capability poor countries receive marginally higher social sectoral aid relative to economic sector aid.

The second chapter introduces a framework to analyze two aid models in Myanmar that imply design key parameters and promote localized aid design. This study finds that the intervention strategies of the revised neo-liberal and the developmental state model differ concerning the main *agency* of change (public vs. private), the handling of *power* (concentration vs. decentralization), and the primary *dimension* of projects (economic vs. social). SMU engages with government extension workers as the main change agent, and its accountability comes from the performance of projects that focus on agricultural production. In contrast, NCDDP works with private facilitators, emphasizing the processes of inclusion in the context of public infrastructure development.

The third chapter combines fine-grained spatial techniques with satellite imagery to assess aid allocation in data-sparse communities in Myanmar. The study indicates that CLD disproportionately flows to better-off villages with higher nightlight luminosity and a lower proportion of vulnerable populations. However, this finer analysis suggests that a need-based allocation is also in place. Aid goes to areas with lower assets within villages of similar levels of nightlights. Among two aid models, NCDDP supports poorer villages farther away from conflict events whereas SMU supports more established areas including villages near conflict zones. Grounding development policy in more contextualized knowledge, billions of aid industry can better serve the "bottom billion."

The three models discussed in this dissertation represent an evolution of the aid landscape over the past three decades. Each era has a dominant way of delivering aid as well as producing evidence with underlying foci of what constitutes development. Changes across these domains delineate the type of aid: sectoral, entrepreneurial and technological [Table 14]. Chapter one discusses sectoral aid; governments in the Northern Hemisphere provide aid to economic and social sectors, considering development gaps of the recipient country. Chapter two describes entrepreneurial aid with an emphasis on cash intervention for individuals or groups of entrepreneurs in developing countries. The case study complements impact evaluations and unveils the black box of operations. The last chapter provides a prospect for technological aid, harnessing novel measurement technologies for social good. One chief feature of incorporating big data into development is that it is primarily gathered, marketed and processed by the private sector (Taylor, 2015).

Table 14. Changing aid landscape

Type	Agenda	Interventions	Actors	Methods	Evidence
Sectoral (Pre-MDGs era-)	Need-aid	Sector-based, Indirect support Education Health Agriculture	Donor states	Cross country panel analysis using IV	Macro, externally valid
Entrepreneurial (MDGs era-)	Aid-Impact	Cash-based, Direct support CCT/UCT CDD Microfinance	Individuals in recipient countries	Experimental studies and meta-analysis Case study	Causal inference & internally valid Why the project works and the black box of design and delivery
Technological (SDG era -)	-Need-aid -Uptake	Conflict & disaster response Social protection Energy ICT Environment & Climate change Health, water	Much of the innovation comes from the private sector (e.g., Silicon Valley)	Non-parametric analysis using big data	Fill data gaps with alternative sources and algorithms Prediction

With the promise of the big data revolution and the need for better information, questions arise over the analytical value and policy relevance of such evidence in the international development context. As illustrated in Figure 12, each method of inquiry illuminates a slightly different aspect of the knowledge continuum, composed of need assessment, implementation, and impact evaluation with each method showing some strengths and weaknesses. Macro analysis addresses bigger need assessment questions at the cost of weaker internal validity. The case study yields a theoretical perspective on why the project did or did not work but such analysis can also cherry-pick evidence. New data collection techniques, such as sensors mounted on cookstoves, can fill the missing link between output and outcome by monitoring adoption patterns of interventions (Wilson et al., 2016). Combing satellite imagery (Jean et al., 2018; Jean et al., 2016) or mobile phone data (Blumenstock et al., 2015; Blumenstock 2016) with deep learning can reasonably assess poverty and needs in the cross-section but has made little progress in estimating changes in welfare over time.[33] Rigorous experimental studies can tease out socio-economic impacts of interventions but are less likely to recover quantities that are useful for policy (Deaton, 2010).

[33] Efforts to measure dynamic poverty prediction such as Derek Chen's "Temporal Poverty Prediction Using Satellite Imagery" have been challenging. Temporal estimations with more data do not necessarily improve poverty predictions than cross-sectional data.

Evaluation continuum along with project cycle

		Process evaluation		Impact evaluation	
	Inputs	Outputs	Monitoring	Outcomes	Policy
Methods	Need Assessment	Product & service design	Uptake of intervention	Socio-economic results	Scaling up
Cross country analysis					
Case study					
Data-intensive measurement techniques					
Survey-based impact evaluation					

Figure 12. Adoption of evidence by measurement models and project cycle

Now, where are the gaps and what is coming next? First of all, it is noted that the impact study-policy link (the right upmost column in Figure 2) is largely missing. Difficulty in comparing evidence from different contexts and unpredictable time spans prevent findings from randomized evaluations from being adopted (Dhaliwal and Tulloch, 2012). The relationship between knowledge production and adoption is also difficult to model given their non-linear, higher-order, and high dimensional interactions. Nonetheless, the advent of the data revolution opens possibilities to discover unforeseen network structures about the research-policy nexus.

The notion of a social-economic planner is embedded in the emerging research with computationally rigorous methods. Big data and the development field are now paying more attention to the context for which algorithms are designed. This line of research is one step further from measurement validation research or conventional analysis with novel measures. For example, if researchers can measure the impact of digital credit on the change in welfare through phone data and surveys, this welfare maximization function can be combined with a profit maximization function (Bjorkegren and Grissen, 2015) to design optimal and precise targeting in an aim to enhance social surplus.

As Figure 12 illustrates, each piece of evidence contributes to creating a complete and holistic sense of evidence. Different methods can be used to inform a distinctive area of evaluation along the project cycle. A good example of combining different methods to tighten the evaluation chain is a Development Engineering project “pay-as-you-go microgrid” in India (Nilsson et al, 2014). The research plans to draw from the geo-coded location of grid infrastructure, electricity usage meter, and pricing experiments. It should also be noted that the feature of knowledge continuum is not unidirectional nor hierarchical. Instead, evidence gained from each stage can be fed back into the integrative design and evaluation process at any other stages.

This study concludes with the need to go back to basics, starting from client and user needs. Impact studies supplemented by big data could transform international development. However, innovations that mostly occur in an engineering lab at the microscopic product level may not be relevant to the priorities of the poor. Many projects failed because they simply did not pass the scrutiny of the very first question: does the intervention take precedence over all competing resources for families and children in extreme deprivation? Similarly, too much emphasis on outcomes can result in disproportionate aid allocation to sectors with easy-to-measure outcomes while stifling innovations with hard-to-reach populations. Relevance to people on the ground should not be forgotten in the use of evidence for development.

REFERENCES

Acemoglu, D., & Robinson, J. A. (2013). *Why nations fail: The origins of power, prosperity, and poverty*. New York, NY: Crown Business.

Alderman, H. (2002). Do local officials know something we don't? Decentralization of targeted transfer in Albania. *Journal of Public Economics, 83*(3), 375–404.

Alesina, A., & Dollar, D. (2000). Who gives foreign aid to whom and why?. *Journal of economic growth*, *5*(1), 33-63.

Alkire, S., & Foster, J. (2011a). Counting and multidimensional poverty measurement. Journal of Public Economics, 95(7), 476-487.

Alkire, S., & Foster, J. (2011b). Understandings and misunderstandings of multidimensional poverty measurement. The Journal of Economic Inequality, 9(2), 289-314.

Alkire, S., & Santos, M. E. (2010). Acute multidimensional poverty: A new index for developing countries. *United Nations development programme human development report office background paper*, (2010/11).25

Amsden, A. H. (1992). *Asia's next giant: South Korea and late industrialization*. Oxford, UK: Oxford University Press on Demand.

Arcand, J. L., & Wagner, N. (2016). Does community-driven development improve inclusiveness in peasant organizations? –Evidence from Senegal. *World Development*, *78*, 105-124.

Batley, R., & Mcloughlin, C. (2010). Engagement with non-state service providers in fragile states: Reconciling state-building and service delivery. *Development Policy Review*, *28*(2), 131-154.

Beath, A., Christia, F., & Enikolopov, R. (2013). Beath, A., Christia, F., & Enikolopov, R. (2013). *Randomized Impact Evaluation of Afghanistan's National Solidarity Programme*. Retrieved from World Bank website: https://openknowledge.worldbank.org/bitstream/handle/10986/16637/811070WP0P11600Box0379828B00PUBLIC0.pdf?sequence=1

Berthélemy, J. C., & Tichit, A. (2004). Bilateral donors' aid allocation decisions—a three-dimensional panel analysis. *International Review of Economics & Finance*, *13*(3), 253-274.

Bertoli, S. & Ticci, E. (2012). A fragile guideline to development assistance. *Development Policy Review*, *30*(2), 211-230.

Blumenstock, J.E., 2016. Fighting poverty with data. Science 353, 753–754. doi:10.1126/science.aah5217

Blumenstock, J., Cadamuro, G., & On, R. (2015). Predicting poverty and wealth from mobile phone metadata. *Science, 350*(6264), 1073-1076.

Booth, D. (2011). Aid, institutions and governance: what have we learned? *Development Policy Review*, *29*(s1), s5-s26.

Briggs, R. C. (2017). Does foreign aid target the poorest?. International Organization, 71(1), 187-206.

Bruederle, A., & Hodler, R. (2018). Nighttime lights as a proxy for human development at the local level. *PloS one*, *13*(9), e0202231.

Buntaine, M. T., Daniels, B., & Devlin, C. (2018). Can information outreach increase participation in community-driven development? A field experiment near Bwindi National Park, Uganda. *World Development*, *106*, 407-421.

Burke, M., Heft-Neal, S., & Bendavid, E. (2016). Sources of variation in under-5 mortality across sub-Saharan Africa: a spatial analysis. *The Lancet Global Health*, *4*(12), e936-e945.

Campbell, T., Peterson, G., & Brakarz, J. (1991). Decentralization to local government in LAC: national strategies and local response in planning, spending and management. Washington DC: The World Bank.

Casey, K., Glennerster, R., & Miguel, E. (2012). Reshaping institutions: Evidence on aid impacts using a pre-analysis plan. *The Quarterly Journal of Economics*, *127*(4), 1755-1812.

Chang, H-J (ed.) 2003. *Rethinking development economics*. London, UK: Anthem.

Chen, X., & Nordhaus, W. D. (2011). Using luminosity data as a proxy for economic statistics. *Proceedings of the National Academy of Sciences*, *108*(21), 8589-8594.

Craig, D., & Porter, D. (2003). Poverty reduction strategy papers: a new convergence. *World Development*, *31*(1), 53-69.

Dasgupta, A., & Beard, V. A. (2007). Community-driven development, collective action and elite capture in Indonesia. *Development and Change*, *38*(2), 229-249.

de Boer, W. F., van Langevelde, F., Prins, H. H., de Ruiter, P. C., Blanc, J., Vis, M. J., & Hamilton, I. D. (2013). Understanding spatial differences in African elephant densities and occurrence, a continent-wide analysis. *Biological Conservation*, *159*, 468-476.

Bradshaw, J., & Finch, N. (2003). Overlaps in dimensions of poverty. *Journal of social policy*, 32(4), 513-525.

Brinkerhoff, D. W. (2011). State fragility and governance: Conflict mitigation and sub-national perspectives. *Development Policy Review*, *29*(2), 131-153.

Dhaliwal, I., & Tulloch, C. (2012). From research to policy: using evidence from impact evaluations to inform development policy. *Journal of Development Effectiveness*, *4*(4), 515-536.

Doll, C. N., Muller, J. P., & Morley, J. G. (2006). Mapping regional economic activity from night-time light satellite imagery. *Ecological Economics*, *57*(1), 75-92.

Donaldson, D., & Storeygard, A. (2016). The view from above: Applications of satellite data in economics. *Journal of Economic Perspectives*, *30*(4), 171-98.

Dongier, P., Van Domelen, J., Ostrom, E., Ryan, A., Wakeman, W., Bebbington, A., & Polski, M. (2003). *Community-driven development*. World Bank Poverty Reduction Strategy Paper. Washington DC: The World Bank.

de Janvry, A., & Sadoulet, E. (2015). *Development Economics: Theory and Practice*. London: Routledge.

Easterly, W. (2014). The tyranny of experts: Economists, dictators, and the forgotten rights of the poor. New York, NY: Basic Books.

Evans, P. B. (1995). *Embedded autonomy: states and industrial transformation* (Vol. 25). Princeton, NJ: Princeton University Press.

Fine, B. (1999). The developmental state is dead—long live social capital? *Development and Change*, *30*(1), 1-19.

François, M. & Sud, I. 2006. Promoting stability and development in fragile and failed states. *Development Policy Review*, 24(2), pp. 141-160.

Fiszbein, A., & Schady, N. R. (2009). *Conditional cash transfers: reducing present and future poverty*. World Bank Publications.

Fritzen, S. A. (2007). Can the design of community-driven development reduce the risk of elite capture? Evidence from Indonesia. *World Development*, 35(8), 1359-1375.

Grindle, M. S. (2011). Good enough governance revisited. *Development Policy Review* *17*(4), 525-548. *25*(5), 533-574.

Gilbert, N., & Terrell, P. (2002). Dimensions of social welfare policy. Boston, MA: Allyn & Bacon.

Grootaert, C., Narayan, D., Jones, V. N., & Woolcock, M. (2004). Measuring social capital: An integrated questionnaire. The World Bank.

Han, S. (2004). The New Community Movement: Park Chung Hee and the Making of State Populism in Korea. *Pacific Affairs, 77*(1), 69-93. Retrieved from http://www.jstor.org/stable/40022275

Haushofer, J., & Shapiro, J. (2016). The short-term impact of unconditional cash transfers to the poor: experimental evidence from Kenya. The Quarterly Journal of Economics, 131(4), 1973-2042.

Hira. A. (2009). State of the State: Does the State Have a Role in Development? Haslam, Schafer and Beaudet (Ed.), *Introduction to International Development: Approaches, Actors, and Issues* (pp. 123-134). Ontario, Canada: Oxford University Press.

Hoff, K., & J. E. Stiglitz. (2001). Modern Economic Theory and Development. In *Frontiers of Development Economics*, ed. G. Meier and J. Stiglitz, 389–459. Oxford, UK: Oxford University Press.

Jean, N., Wang, S., Azzari, G., Lobell, D., & Ermon, S. (2018). Tile2Vec: Unsupervised representation learning for remote sensing data. *arXiv preprint arXiv:1805.02855*.

Jean, N., Burke, M., Xie, M., Davis, W. M., Lobell, D. B., & Ermon, S. (2016). Combining satellite imagery and machine learning to predict poverty. *Science*, *353*(6301), 790-794.

Johnson, C. (1982). MITI and the Japanese miracle: the growth of industrial policy: 1925-1975. Palo Alto, CA: Stanford University Press.
References

Johnson, C., Deshingkar, P., Farrington, J., & Start, D. (2007). Does Devolution Deliver? Institutional and Political Dimensions of Self-help Programmes in India. IDS Bulletin, 38(1), 33-44.

Jolliffe, K. (2015). Ethnic armed conflict and territorial administration in Myanmar. *The Asia Foundation*, 89.

Jung, W. (2014). Korea's development assistance in fragile states: What is at stake? Howe, B., M. (ed.) 2013. *Post-Conflict Development in East Asia*. Farnham, UK: Ashgate Publishing, Limited.

Jung. W. (2012). Pro-Poor Delivery of Aid, Korea International Cooperation Agency, Seoul.

Hayek, F. A. (2014). *The road to serfdom: Text and documents: The definitive edition*. London, UK: The University of Chicago Press Routledge.

Henderson, J. V., Storeygard, A., & Weil, D. N. (2012). Measuring economic growth from outer space. *American economic review*, *102*(2), 994-1028.

Laderchi, C. R., Saith, R., & Stewart, F. (2003). Does it Matter that we do not Agree on the Definition of Poverty? A Comparison of Four Approaches. *Oxford Development Studies*, *31*(3), 243–274. doi:10.1080/1360081032000111698

Milusheva, S., 2016. *Less Bite for your Buck: Using Cell Phone Data to Target Disease Prevention*. Working Paper

Mullainathan, S. (2016, April, 1). Satellite images can pinpoint poverty where surveys can't, *New York Times*. Retrieved from http://www.nytimes.com/2016/04/03/upshot/satellite-images-canpinpoint-poverty-where-surveys-cant.html?_r=0

Myrdal, G. (1974). What is development?. *Journal of Economic Issues*, *8*(4), 729-736.

Nilsson, L., Madon, T., & Sastry, S. S. (2014). Toward a new field of development engineering: linking technology design to the demands of the poor. *Procedia Engineering*, *78*, 3-9.

Nunn, N., & Qian, N. (2014). US food aid and civil conflict. *The American Economic Review*, *104*(6), 1630-1666.

Nussbaum, M. (2000). Women's capabilities and social justice. *Journal of Human Development*, 1(2), 219-247.

Roelen, K. (2017), Monetary and Multidimensional Child Poverty: A Contradiction in Terms? *Development and Change*, 48: 502–533. doi:10.1111/dech.12306

Roodman, D. (2009). *A note on the theme of too many instruments*. Oxford Bulletin of Economics and statistics, 71(1), 135-158.

Klasen, S. (2008). Economic Growth and Poverty Reduction: Measurement Issues using Income and Non-Income Indicators. World Development, 36(3), 420–445. doi:10.1016/j.worlddev.2007.03.008

Kakwani, N., & Silber, J. (2008). Introduction: multidimensional poverty analysis: conceptual issues, empirical illustrations and policy implications. World Development, 36(6), 987-991.

Kenny, C., & Dykstra, S. (2013). The global partnership for development: A review of MDG 8 and proposals for the post-2015 development agenda.

Korea Rural Community Corporation (KRCC) and Korea International Cooperation Agency (KOICA). (2016). *Master plan*. Seongnam, Korea: Korea International Cooperation Agency.

Krueger, A. O. (2000). *Economic policy reform: the second stage*. Chicago, IL: University of Chicago Press.

Labonne., J. (2013). Myanmar CDD Project: Impact evaluation feasibility note. The World Bank.

Labonne, J., & Chase, R. S. (2011). Do community-driven development projects enhance social capital? Evidence from the Philippines. *Journal of Development Economics*, 96(2), 348–358. doi:10.1016/j.jdeveco.2010.08.016

Kidd, S. & Athia, D. (2019). *Hit and miss: An assessment of targeting effectiveness in social protection*. Working paper. Development Pathways.

Kohli, A. (2004). State-directed development: political power and industrialization in the global periphery. Cambridge, UK: Cambridge University Press.

Mansuri, G., & Rao, V. (2012). *Localizing development: Does participation work?* Washington, DC: The World Bank.

Mansuri, G., & Rao, V. (2004). Community-based and -driven Development: A critical review. *The World Bank Research Observer*, 19(1), 1–39.

Matarrita-Cascante, D., & Brennan, M. A. (2012). Conceptualizing community development in the twenty-first century. *Community Development*, *43*(3), 293–305. doi:10.1080/15575330.2011.593267

Mattessich, P. W., Murray-Close, M., & Monsey, B. (2004). Collaboration: What makes it work: A review of research literature on factors influencing successful collaboration. St Paul, MN: Amherst H. Wilder Foundation.

Mohan, G., & Stokke, K. (2000). Participatory development and empowerment: the dangers of localism. *Third World Quarterly*, *21*(2), 247-268.

Mosse, D. (2005). Cultivating development: An ethnography of aid policy and practice. London, UK: Pluto Press.

Nunn, N., & Qian, N. (2014). US food aid and civil conflict. *The American Economic Review*, *104*(6), 1630-1666.

OECD (2007). Principles for good international engagement in fragile states & situations. Paris, France: OECD.

Platteau, J. P., & Abraham, A. (2002). Participatory development in the presence of endogenous community imperfections. *Journal of Development Studies, 39*(2), 104-136.

Platteau, J. P., & Gaspart, F. (2003). The risk of resource misappropriation in community-driven development. *World development*, *31*(10), 1687-1703.

Qian, N. (2014). *Making progress on foreign aid* (No. w20412). National Bureau of Economic Research.

Rao, V., & Ibáñez, A. M. (2005). The social impact of social funds in Jamaica: A "Participatory econometric" analysis of targeting, collective action, and participation in community-driven development. *Journal of Development Studies*, 41(5), 788–838. doi:10.1080/00220380500145297

Reed, E. P. (2010, September). *Is Saemaul undong a model for developing countries today?* Paper presented at the Anniversary of Saemaul Undong hosted by the Korea Saemaul Undong Center. Seoul, Korea.

Sachs, J. D. (2006). The end of poverty: economic possibilities for our time. New York, NY: Penguin Books.

Sahn, D. E., & Stifel, D. (2003). Exploring alternative measures of welfare in the absence of expenditure data. *Review of income and wealth*, *49*(4), 463-489.

Sen, A. (1999). *Development as freedom*. New York: Alfred Knopf.

Sen, A. (1976). Poverty: an ordinal approach to measurement.*Econometrica: Journal of the Econometric Society*, 219-231.

Steiner, S. (2007). Decentralisation and poverty: conceptual framework and application to Uganda. *Public Administration and Development*, *27(2),* 175-185.

Stiglitz, J. E. (2002). *Globalization and its discontents*. New York, NY: Norton.

Sumner, A. (2013). Poverty, Politics and Aid: is a reframing of global poverty approaching? *Third World Quarterly*, *34*(3), 357–377. doi:10.1080/01436597.2013.784593

Tran, V. Q., Alkire, S., & Klasen, S. (2015). Static and dynamic disparities between monetary and multidimensional poverty measurement: Evidence from Vietnam. In Measurement of Poverty, Deprivation, and Economic Mobility (pp. 249-281). Emerald Group Publishing Limited.

Taylor, L. (2016). No place to hide? The ethics and analytics of tracking mobility using mobile phone data. Environment and Planning D: Society and Space, 34(2), 319-336.

Van Der Gaag, M., & Snijders, T. A. B. (2005). The Resource Generator: social capital quantification with concrete items. *Social Networks*, *27*(1), 1–29.

Wallace, T. (2009). NGO dilemmas: Trojan horses for global neoliberalism? *Socialist Register*, *40*(40).

Wade, R. (1990). Governing the market: Economic theory and the role of government in East Asian industrialization. Princeton, NJ: Princeton University Press.

White, H., Menon, R., & Waddington, H. (2018). *Community-driven development: does it build social cohesion or infrastructure? A mixed-method evidence synthesis*. Technical Report. New Delhi, India: International Initiative for Impact Evaluation (3ie).

Wilson, D. L., Coyle, J., Kirk, A., Rosa, J., Abbas, O., Adam, M. I., & Gadgil, A. J. (2016). Measuring and increasing adoption rates of cookstoves in a humanitarian crisis. *Environmental science & technology*, *50*(15), 8393-8399.

Winthrop, R., Bulloch, G., Bhatt, P., & Wood, A. (2015). Development Goals in an Era of Demographic Change. *Global Monitoring Report*, *2016*.

Wong, S. (2012). What have been the impacts of World Bank Community-Driven Development Programs? CDD impact evaluation review and operational and research implications (Report No. 69541). Washington, DC: The World Bank. Retrieved from http://documents.worldbank.org/curated/en/2012/03/16374801/impacts-world-bank-community-driven-development-programs-cdd-impact-evaluation-review-operational-research-implications

Woo-Cumings, M. (1999). The developmental state. Ithaca, NY: Cornell University Press.

The World Bank. (2015). National community-driven development project. Operational Manual. Washington, DC: The World Bank.

The World Bank (2012). Emergency project paper on a proposed pre-arrears clearance grant in the amount of SDR 52.6 million to the Republic of the Union of Myanmar for a National community-driven development project (Report No. 72460-MM). Washington, DC: The World Bank.

APPENDICES

Appendix A. Correlation Matrix of Income Poverty Headcounts and MPI Headcounts

Pearson

	P_0	M_0 (MPI)	Mpovr (H)	Intensity (A)
P_0	1	0.7516531	0.7748787	0.5967332
M_0 (MPI)	0.7516531	1	0.9895677	0.8688045
Mpovr (H)	**0.7748787**	**0.9895677**	1	0.8504792
Intensity (A)	0.5967332	0.8688045	0.8504792	1

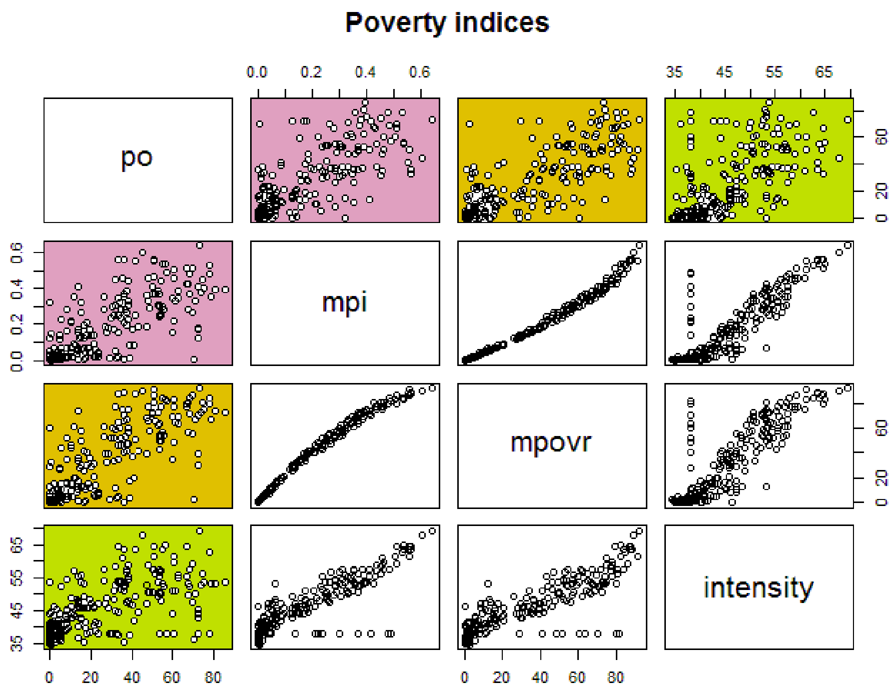
	P_0	schooling	attend	mortality	nutrition	electricity	sanitation	water	flooring	fuel	asset
P_0	1	0.5846509	0.5595143	0.7273057	0.5250655	0.7882454	0.7309043	0.7407611	0.6883805	0.7664692	0.7096551
schooling	0.5846509	1	0.8831938	0.8312767	0.6609588	0.8543223	0.8609468	0.7765004	0.7772514	0.8714353	0.7592103
attend	**0.5595143**	0.8831938	1	0.845522	0.7045426	0.8175778	0.8347958	0.7442113	0.7349236	0.8424292	0.6796785
mortality	0.7273057	0.8312767	0.845522	1	0.7769616	0.9183382	0.9114942	0.846071	0.8342368	0.9393274	0.7722635
nutrition	0.5250655	0.6609588	0.7045426	0.7769616	1	0.7291714	0.7562667	0.6436039	0.7258917	0.7979812	0.6113137
electricity	**0.7882454**	0.8543223	0.8175778	0.9183382	0.7291714	1	0.9610621	0.9308456	0.8944433	0.9780346	0.8818685
sanitation	0.7309043	0.8609468	0.8347958	0.9114942	0.7562667	0.9610621	1	0.9061214	0.8677847	0.9736016	0.8785764
water	0.7407611	0.7765004	0.7442113	0.846071	0.6436039	0.9308456	0.9061214	1	0.8454265	0.9043871	0.8690192
flooring	0.6883805	0.7772514	0.7349236	0.8342368	0.7258917	0.8944433	0.8677847	0.8454265	1	0.8949625	0.8550929
fuel	**0.7664692**	0.8714353	0.8424292	0.9393274	0.7979812	0.9780346	0.9736016	0.9043871	0.8949625	1	0.8731369
asset	0.7096551	0.7592103	0.6796785	0.7722635	0.6113137	0.8818685	0.8785764	0.8690192	0.8550929	0.8731369	1

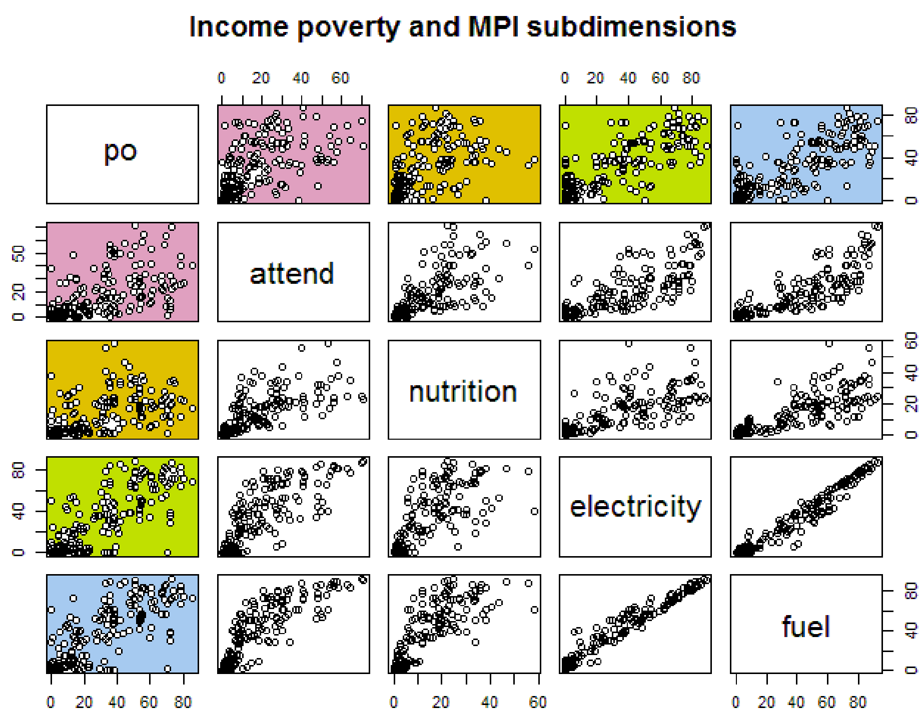
Spearman

	P_0	M_0 (MPI)	Mpovr (H)	Intensity (A)
P_0	1	0.7778971	0.783985	0.6178183
M_0 (MPI)	0.7778971	1	0.9982707	0.850475
Mpovr (H)	**0.783985**	0.9982707	1	0.8400715
Intensity (A)	0.6178183	0.850475	0.8400715	1

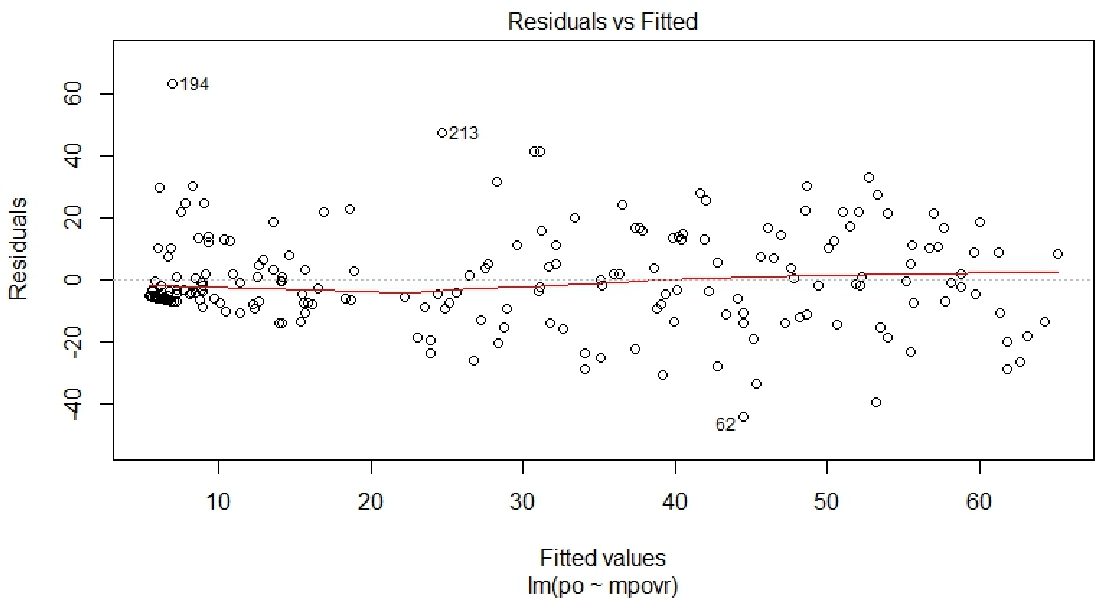
	P_0	schooling	attend	mortality	nutrition	electricity	sanitation	water	flooring	fuel	asset
P_0	1	0.661307	0.6738517	0.7559161	0.6193097	0.7856509	0.7425859	0.7590804	0.7335269	0.7636743	0.7650843
schooling	**0.661307**	1	0.9020084	0.8859818	0.7795386	0.8950859	0.9047944	0.8360254	0.818878	0.9145069	0.8285399
attend	0.7559161	0.8859818	0.9092955	1	0.8575307	0.9333714	0.9285584	0.8938954	0.8780826	0.9513226	0.8429288
mortality	0.7559161	0.8859818	0.9092955	1	0.8575307	0.9333714	0.9285584	0.8938954	0.8780826	0.9513226	0.8429288
nutrition	0.6193097	0.7795386	0.8242178	0.8575307	1	0.81484	0.8252994	0.7632894	0.818339	0.8538255	0.7512793
electricity	**0.7856509**	0.8950859	0.8834053	0.9333714	0.81484	1	0.9635303	0.9435207	0.91089	0.9790772	0.9168439
sanitation	0.7425859	0.9047944	0.8963606	0.9285584	0.8252994	0.9635303	1	0.9251209	0.8905333	0.9704679	0.9098563
water	0.7590804	0.8360254	0.8512159	0.8938954	0.7632894	0.9435207	0.9251209	1	0.8751811	0.9235903	0.8965077
flooring	0.7335269	0.818878	0.8229266	0.8780826	0.818339	0.91089	0.8905333	0.8751811	1	0.9205089	0.890198
fuel	**0.7636743**	0.9145069	0.9045422	0.9513226	0.8538255	0.9790772	0.9704679	0.9235903	0.9205089	1	0.907033
asset	0.7650843	0.8285399	0.7988218	0.8429288	0.7512793	0.9168439	0.9098563	0.8965077	0.890198	0.907033	1

Appendix B. Scatterplot of Poverty Indices





Appendix C. Residual Plot of the Linear Regression Model of P0 predicted by H



Appendix D. Descriptive Statistics of Variables

Source	Classification	Variable explanation	Variable names	Number Of Observa-tion	Mean	Std. Dev.	Min	Max
-	Discrepancy	residuals of H & Po	residv	213	1.12E-09	15.42389	-44.45582	63.51445
-	Discrepancy	residuals of ln(H) & Po	resid	213	-9.02E-09	18.00587	-41.22289	61.637
WDI	Income poverty	poverty headcount ratio at 1.90 a day, 2011 PPP(Po, and national) (%)	po	213	28.28384	24.40064	0	85.94875
Oxford /UNDP	Multidimensional poverty	MPI (Mo)	mpi	213	0.1891408	0.1735745	0	0.642
Oxford /UNDP	Multidimensional poverty	MPI (H) multidimensional headcount ratio (%)	mpovr	213	35.35775	29.27826	0	92.4
Oxford /UNDP	Multidimensional poverty	MPI (A) intensity	intensity	213	46.62817	8.131389	34.4	69.4
Oxford /UNDP	Multidimensional poverty	ln(H)	lnm	213	2.7981	1.658399	-4.60517	4.526235
WDI	Country characteristics	Gross national per capita income in constant 2005 USD	gnipc	208	4890.913	3911.525	490	16690
WDI	Country characteristics	GDP annual growth (%)	growth	211	5.261505	4.153829	-5.51144	34.5
WDI	Country characteristics	External debt shocks total, public and publicly guaranteed in constant 2005 USD	debt	202	1.69E+09	5.08E+09	2000000	3.90E+10
WDI	Country characteristics	population count	pop	213	4.76E+07	1.54E+08	137164	1.40E+09
WDI	Country characteristics	adult literacy rate	literacy	61	70.349	22.52636	15.4567	98.257
WDI	Country characteristics	life expectancy at birth in total years	life	213	63.83794	8.761634	42.8107	76.6521
WDI	Country characteristics	CPIA overall rating (1-6) indicating good governance	policy	124	3.339651	0.4336812	1.76667	4.33333
WDI	Country characteristics	GINI cofficient	gini	64	41.92266	9.981263	24.74	63.01
EM-DAT	Country characteristics	Total number of affected people by natural disaster	affect	152	3361565	2.37E+07	0	2.85E+08

Oxford /UNDP	MPI sub indicators: Education	years of schooling (%)	schooling	213	15.5615	16.68507	0	66.3
Oxford /UNDP	MPI sub indicators: Education	child school attendance	attend	202	16.30545	17.2613	0	71
Oxford /UNDP	MPI sub indicators: Health	child mortality	mortality	200	18.762	16.17558	0	57.8
Oxford /UNDP	MPI sub indicators: Health	nutrition (%)	nutrition	194	12.51753	12.55719	0	58.5
Oxford /UNDP	MPI sub indicators: Living Standards	improved sanitation (%)	sanitation	213	28.89953	26.55746	0	89.3
Oxford /UNDP	MPI sub indicators: Living Standards	drinking water	water	213	19.11268	18.99817	0	65.5
Oxford /UNDP	MPI sub indicators: Living Standards	flooring	flooring	206	23.38544	24.90118	0	86.5
Oxford /UNDP	MPI sub indicators: Living Standards	cooking fuel	fuel	205	33.87415	29.85254	0	92.3
Oxford /UNDP	MPI sub indicators: Living Standards	asset ownership	asset	212	20.8684	21.32799	0	87.5
Oxford /UNDP	MPI sub indicators: Living Standards	electricity	electricity	209	28.71053	28.5589	0	88.7
AidData/ OECD CRS	The ratio of social to economic sector aid by country by year	annual social sector aid /annual economic sector aid , commitment amount, USD in constant 2014 USD	sec1sec2	124	33.00412	139.2319	0.2584969	1392.204
AidData/ OECD CRS	The ratio of social to economic and production sector aid by country by year	annual social sector aid /(annual economic sector + production sector aid) , commitment amount, USD in constant 2014 USD	sec1sec2sec3	123	4.544119	9.667077	0.2397078	74.79219
WB country classification	Categorical /dummy variable, time invariant	Region: EAP (East Asia and Pacific), ECA (Europe and Central Asia) LAC (Latin America & Caribbean), SA (South Asia), SSA (Sub-Saharan Africa), MENA (Middle East & North Africa).	region	213	EAP 9.39%, ECA 14.08%, LAC 17.37%, MNA 8.92%, SAS 6.57%, SSA 43.66%, (Reference group-SSA)	-	-	-
WB country classification	Categorical / dummy variable	Income classification: UM (Upper middle income), LM (Lower middle income), L (Low income)	class	213	UM 14.55%, LM 42.25%, L 43.19% (Reference group - L)	-	-	-

Appendix E. Classification of Countries by Salient Dimension of Poverty

Country name	Country code & year	Discrepancy (residual value)	Binary classification (Not strict)	Countries with residual value of ±1 standard deviation (Medium)	Countries with residual value of ±2 standard deviation (Strict)
Afghanistan	AFG10	-12.2763873	cpoor	poor	poor
Angola	AGO01	-23.4229587	cpoor	cpoor	poor
Albania	ALB05	-4.9760336	cpoor	poor	poor
	ALB08	-5.9843487	cpoor	poor	poor
Armenia	ARM05	-1.7106126	cpoor	poor	poor
	ARM10	-3.1039823	cpoor	poor	poor
Azerbaijan	AZE06	-8.8729204	cpoor	poor	poor
Burundi	BDI05	18.4394522	ipoor	ipoor	poor
	BDI10	16.7851154	ipoor	ipoor	poor
Benin	BEN06	-1.370298	cpoor	poor	poor
	BEN11	7.4917651	ipoor	poor	poor
Burkina Faso	BFA06	-2.5173033	cpoor	poor	poor
	BFA10	-4.7347379	cpoor	poor	poor
Bangladesh	BGD07	5.6312317	ipoor	poor	poor
	BGD11	3.4848502	ipoor	poor	poor
	BGD12	10.9398768	ipoor	poor	poor
	BGD14	5.1847264	ipoor	poor	poor
Bosnia and Herzegovina	BIH06	-5.8668761	cpoor	poor	poor
	BIH11	-5.7731398	cpoor	poor	poor
Belarus	BLR05	-5.090246	cpoor	poor	poor
Belize	BLZ06	1.8433413	ipoor	poor	poor
	BLZ11	0.3391273	ipoor	poor	poor
Bolivia	BOL03	-9.5973366	cpoor	poor	poor
	BOL08	-6.7788922	cpoor	poor	poor
Brazil	BRA03	1.7705592	ipoor	poor	poor
	BRA06	0.7461275	ipoor	poor	poor
	BRA14	-3.7229208	cpoor	poor	poor
Bhutan	BTN10	-18.5156692	cpoor	cpoor	poor
Central African Republic	CAF00	8.8418818	ipoor	poor	poor
	CAF10	11.3066318	ipoor	poor	poor
China	CHN02	18.4274098	ipoor	ipoor	poor

	CHN12	-1.0983406	cpoor	poor	poor
Cote d'Ivoire	CIV05	-19.1411835	cpoor	cpoor	poor
	CIV11	-11.3429792	cpoor	poor	poor
Cameroon	CMR04	-13.6757251	cpoor	poor	poor
	CMR11	-1.7864764	cpoor	poor	poor
Congo, Rep.	COG09	4.2107767	ipoor	poor	poor
	COG11	-2.3780155	cpoor	poor	poor
Colombia	COL05	-0.9914921	cpoor	poor	poor
	COL10	-0.8774988	cpoor	poor	poor
Comoros	COM00	-39.703951	cpoor	cpoor	cpoor
	COM12	-15.2286003	cpoor	poor	poor
Djibouti	DJI06	-4.6658242	cpoor	poor	poor
Dominican Republic	DOM00	-7.1584886	cpoor	poor	poor
	DOM07	-4.0808689	cpoor	poor	poor
	DOM13	-6.423763	cpoor	poor	poor
Ecuador	ECU03	10.0690222	ipoor	poor	poor
	ECU13	-3.2159241	cpoor	poor	poor
Egypt, Arab Rep.	EGY08	12.2750283	ipoor	poor	poor
	EGY14	24.6249206	ipoor	ipoor	poor
Ethiopia (excludes Eritrea)	ETH05	-26.818694	cpoor	cpoor	poor
	ETH11	-28.7491711	cpoor	cpoor	poor
Gabon	GAB00	-20.3411279	cpoor	cpoor	poor
	GAB12	-8.1357419	cpoor	poor	poor
Georgia	GEO05	10.2531229	ipoor	poor	poor
Ghana	GHA08	-4.1988207	cpoor	poor	poor
	GHA11	-7.4321916	cpoor	poor	poor
	GHA14	-13.3132917	cpoor	poor	poor
Guinea	GIN05	1.7322755	ipoor	poor	poor
	GIN12	-18.6788961	cpoor	cpoor	poor
Gambia, The	GMB05	-10.5698181	cpoor	poor	poor
	GMB13	-44.4558181	cpoor	cpoor	cpoor
	GNB06	4.9762136	ipoor	poor	poor
Guatemala	GTM03	-5.6661453	cpoor	poor	poor
Guyana	GUY05	-14.1038001	cpoor	poor	poor
	GUY09	-10.4228107	cpoor	poor	poor

Honduras	HND05	1.3516574	ipoor	poor	poor
	HND11	3.0963096	ipoor	poor	poor
Haiti	HTI05	13.1064233	ipoor	poor	poor
	HTI06	12.9536963	ipoor	poor	poor
	HTI12	16.5578457	ipoor	ipoor	poor
India	IDN07	2.5207055	ipoor	poor	poor
	IDN12	-4.9499561	cpoor	poor	poor
	IND05	-3.1230401	cpoor	poor	poor
Iraq	IRQ06	7.7795698	ipoor	poor	poor
	IRQ11	6.5419506	ipoor	poor	poor
Jamaica	JAM10	-6.7418212	cpoor	poor	poor
	JAM12	-6.6126637	cpoor	poor	poor
Jordan	JOR07	-6.9738726	cpoor	poor	poor
	JOR09	-6.8701363	cpoor	poor	poor
	JOR12	-6.418085	cpoor	poor	poor
Kazakhstan	KAZ06	-5.2177186	cpoor	poor	poor
	KAZ10	-5.4594035	cpoor	poor	poor
Kenya	KEN03	-13.8808192	cpoor	poor	poor
	KEN08	1.8186038	ipoor	poor	poor
	KEN14	15.995325	ipoor	ipoor	poor
Kyrgyz Republic	KGZ05	13.3453937	ipoor	poor	poor
	KGZ12	-3.8318211	cpoor	poor	poor
	KGZ14	-0.6431394	cpoor	poor	poor
Cambodia	KHM05	-7.9312022	cpoor	poor	poor
	KHM10	-25.1218974	cpoor	cpoor	poor
	KHM14	-26.1912363	cpoor	cpoor	poor
Lao PDR	LAO06	1.6545774	ipoor	poor	poor
	LAO11	3.7483962	ipoor	poor	poor
Liberia	LBR07	9.0081718	ipoor	poor	poor
	LBR13	17.2096746	ipoor	ipoor	poor
St. Lucia	LCA12	29.7339684	ipoor	ipoor	poor
Sri Lanka	LKA03	-1.7054203	cpoor	poor	poor
Lesotho	LSO04	24.3823706	ipoor	ipoor	poor
	LSO09	31.6109531	ipoor	ipoor	ipoor
Morocco	MAR03	-19.4237647	cpoor	cpoor	poor

	MAR07	-9.1755949	cpoor	poor	poor
	MAR10	-13.586804	cpoor	poor	poor
Moldova	MDA05	7.2727575	ipoor	poor	poor
	MDA12	-5.6268761	cpoor	poor	poor
Madagascar	MDG04	21.7367249	ipoor	ipoor	poor
	MDG08	30.0265623	ipoor	ipoor	poor
Maldives	MDV09	-3.2183414	cpoor	poor	poor
	MEX06	-4.7433965	cpoor	poor	poor
MExico	MEX12	-4.5784512	cpoor	poor	poor
Madagascar	MKD05	-5.2972425	cpoor	poor	poor
	MKD11	-5.9022973	cpoor	poor	poor
Mali	MLI06	-10.7954517	cpoor	poor	poor
	MLI12	-7.7079459	cpoor	poor	poor
Montenegro	MNE05	-6.1689274	cpoor	poor	poor
	MNE13	-3.9539822	cpoor	poor	poor
	MNG05	-10.6296903	cpoor	poor	poor
	MNG10	-10.6314921	cpoor	poor	poor
Mozambique	MOZ03	21.4392351	ipoor	ipoor	poor
	MOZ09	10.1421269	ipoor	poor	poor
	MOZ11	12.5329318	ipoor	poor	poor
Mauritania	MRT07	-33.5153421	cpoor	cpoor	cpoor
	MRT11	-30.8603602	cpoor	cpoor	cpoor
Mauritania	MWI04	21.6184637	ipoor	ipoor	poor
	MWI10	22.3857239	ipoor	ipoor	poor
	MWI13	27.9356544	ipoor	ipoor	poor
Namibia	NAM06	-3.9934357	cpoor	poor	poor
	NAM13	-15.879991	cpoor	cpoor	poor
Niger	NER06	8.3539761	ipoor	poor	poor
	NER12	-18.1990793	cpoor	cpoor	poor
Nigeria	NGA03	7.0022392	ipoor	poor	poor
	NGA08	13.0809778	ipoor	poor	poor
	NGA11	20.0604851	ipoor	ipoor	poor
	NGA13	13.6705217	ipoor	poor	poor
Nicaragua	NIC01	-14.1438021	cpoor	poor	poor
	NIC06	-9.1247993	cpoor	poor	poor

	NIC11	-7.402427	cpoor	poor	poor
Nicaragua	NPL06	-13.9227039	cpoor	poor	poor
	NPL11	-23.6340587	cpoor	cpoor	poor
	NPL14	-23.9197719	cpoor	cpoor	poor
Pakistan	PAK06	-22.4821543	cpoor	cpoor	poor
	PAK12	-28.9940584	cpoor	cpoor	poor
Peru	PER04	-6.0814196	cpoor	poor	poor
	PER08	-7.6491115	cpoor	poor	poor
	PER12	-8.1010159	cpoor	poor	poor
Philippines	PHL03	3.25283	ipoor	poor	poor
	PHL08	-0.6338001	cpoor	poor	poor
	PHL13	0.9327562	ipoor	poor	poor
Paraguay	PRY02	-0.7292213	cpoor	poor	poor
Rwanda	RWA05	10.757587	ipoor	poor	poor
	RWA10	10.2404083	ipoor	poor	poor
	RWA14	13.8563801	ipoor	poor	poor
Sudan	SDN10	-27.8567703	cpoor	cpoor	poor
Senegal	SEN05	-11.0734357	cpoor	poor	poor
	SEN10	-15.5835118	cpoor	cpoor	poor
	SEN12	-6.0216796	cpoor	poor	poor
	SEN14	-4.0155635	cpoor	poor	poor
Sierra Leone	SLE05	-1.0569359	cpoor	poor	poor
	SLE08	-0.4983916	cpoor	poor	poor
	SLE10	0.8426537	ipoor	poor	poor
	SLE13	-6.9940411	cpoor	poor	poor
Serbia	SRB05	-4.8868761	cpoor	poor	poor
	SRB10	-5.4148248	cpoor	poor	poor
	SRB14	-5.5594035	cpoor	poor	poor
South Sudan	SSD10	-13.6815	cpoor	poor	poor
Sao Tome and Principe	STP00	-9.2628871	cpoor	poor	poor
	STP08	5.2840812	ipoor	poor	poor
	SUR00	13.0863459	ipoor	poor	poor
Suriname	SUR06	12.6342945	ipoor	poor	poor
	SUR10	14.119606	ipoor	poor	poor
Swaziland	SWZ07	11.2685896	ipoor	poor	poor

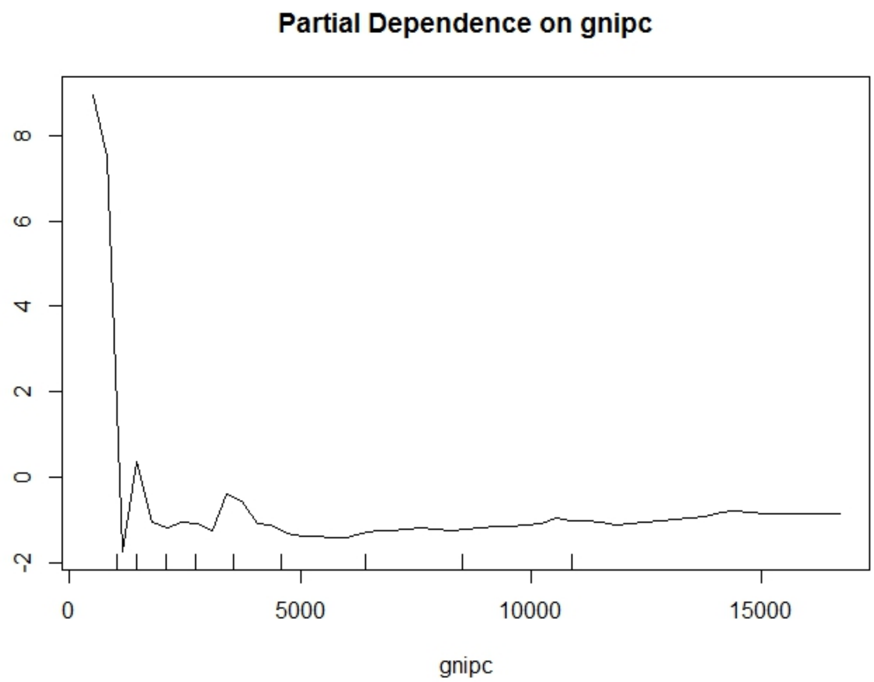
	SWZ10	22.6934636	ipoor	ipoor	poor
Syrian Arab Republic	SYR06	24.4979231	ipoor	ipoor	poor
	SYR09	30.3082895	ipoor	ipoor	poor
Chad	TCD03	16.8697118	ipoor	ipoor	poor
	TCD10	-20.2691763	cpoor	cpoor	poor
Togo	TGO06	15.0334853	ipoor	poor	poor
	TGO10	16.8435306	ipoor	ipoor	poor
	TGO13	15.8277953	ipoor	ipoor	poor
Thailand	THA05	-5.7635062	cpoor	poor	poor
Tajikistan	TJK05	-2.7565473	cpoor	poor	poor
	TJK12	-13.9746426	cpoor	poor	poor
Turkmenistan	TKM06	-6.6772425	cpoor	poor	poor
	TMP09	-1.8217188	cpoor	poor	poor
Turkey	TUN03	-3.2764513	cpoor	poor	poor
	TUN11	-4.4551912	cpoor	poor	poor
	TUR03	-5.9724443	cpoor	poor	poor
Tanzania	TZA08	3.6419003	ipoor	poor	poor
	TZA10	0.3185852	ipoor	poor	poor
	UGA06	-1.8906908	cpoor	poor	poor
Uganda	UGA11	-14.6107995	cpoor	poor	poor
Ukraine	UKR07	-6.8309788	cpoor	poor	poor
	UKR12	-6.2251912	cpoor	poor	poor
	UZB06	63.5144475	ipoor	ipoor	ipoor
Vietnam	VNM02	21.8993122	ipoor	ipoor	poor
	VNM11	-4.1575539	cpoor	poor	poor
	VNM13	-7.5803382	cpoor	poor	poor
Vanuatu	VUT07	-9.5284533	cpoor	poor	poor
West Bank and Gaza or Palestine	WBG10	-6.4189274	cpoor	poor	poor
	WBG14	-6.1606124	cpoor	poor	poor
Yemen	YEM06	-4.554097	cpoor	poor	poor
	YEM13	-0.2918987	cpoor	poor	poor
South Africa	ZAF03	21.7128124	ipoor	ipoor	poor
	ZAF08	0.9661999	ipoor	poor	poor
	ZAF12	4.4381774	ipoor	poor	poor
Congo, Dem. Rep.	ZAR07	33.2268503	ipoor	ipoor	ipoor

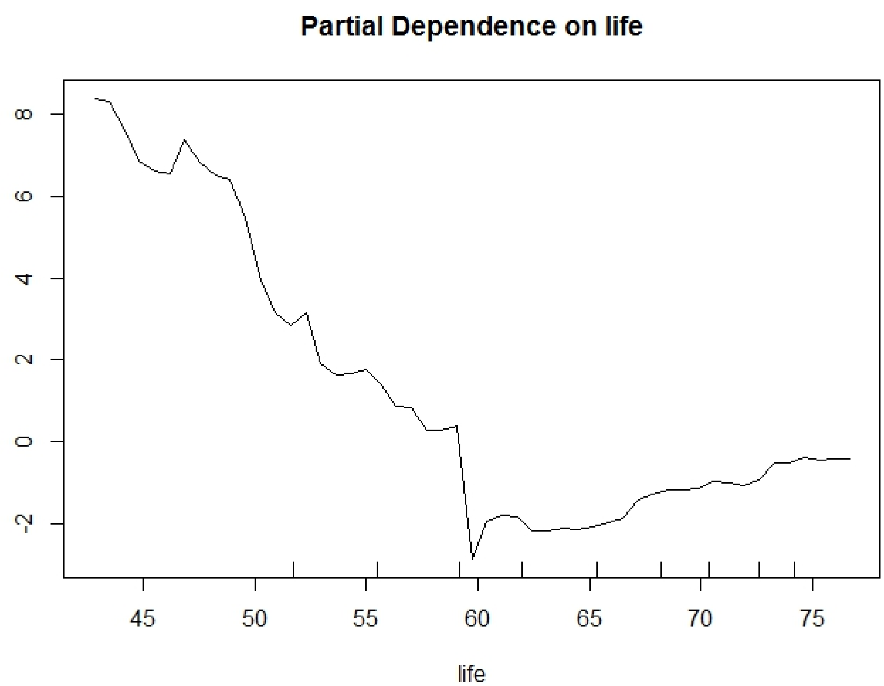
	ZAR10	27.4489702	ipoor	ipoor	poor
	ZAR13	21.4773539	ipoor	ipoor	poor
Zambia	ZMB07	14.5426879	ipoor	poor	poor
	ZMB13	25.4056758	ipoor	ipoor	poor
Zimbabwe	ZWE06	41.2119886	ipoor	ipoor	ipoor
	ZWE10	41.5994611	ipoor	ipoor	ipoor
	ZWE14	47.6698647	ipoor	ipoor	ipoor

Appendix F. Variable Importance and Partial Dependence Plots

%IncMSE	IncNode	Purity
communist	1.43	321.58
gnipc	20.40	7005.88
pop	10.67	4839.60
region_long	7.55	2103.46
gini	2.57	765.35
policy	8.20	3203.66
damage	5.25	903.76
structure	8.84	4321.81
social	6.41	2251.00
economic	7.03	2682.10
public	8.00	3241.19
literacy	10.27	2989.54
life	17.33	5986.73
affect	3.17	3429.34
death	1.19	2684.67

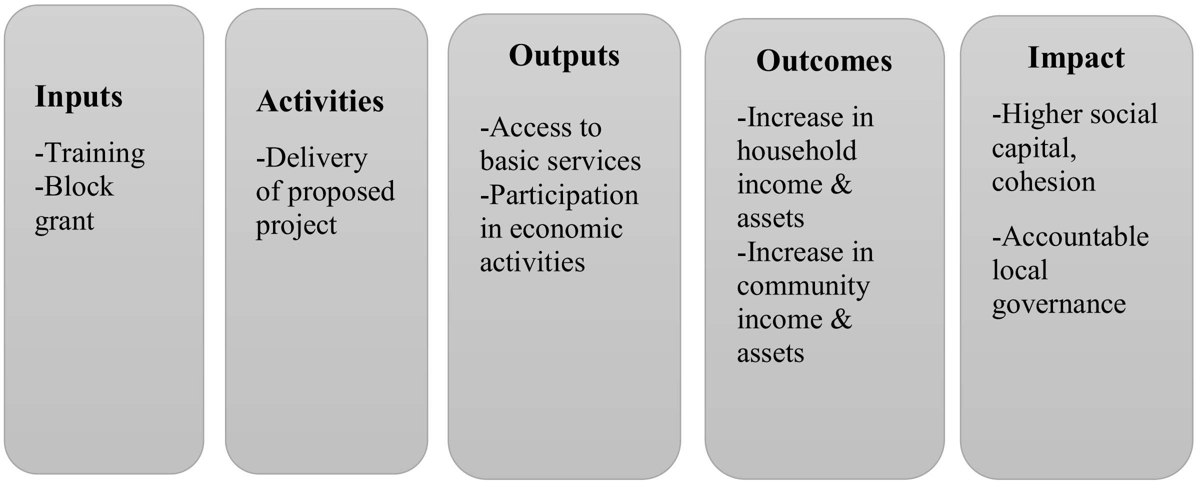
Notes: This analysis uses a Random forest algorithm with country characteristics including income, growth, debt, inequality, overall CPIA scores, and four sub-cluster scores, vulnerability to disaster, region, life expectancy, and adult literacy. As a default, results are obtained from 500 trees with 5 variables tried at each split. The model entered with the above-mentioned covariates can explain approximately 11.82% of the variation in residuals. These variables are not directly linked with indicators that are used to create the MPI indices or poverty rate, but they are only indirectly related with P_0 or MPI variables. This process, therefore, involves reverse engineering of P_0, H, and the difference between income and capability measures. A representation of the variable importance in the dataset is shown in table 4. It summarizes the importance of each predictor. The variables with the largest mean decrease in GINI is GNI per capita (20.4%) and life expectancy (10.27%). Interestingly, these two variables represent two crucial aspects of income and multidimensional poverty.





Notes: For the two most relevant measures, partial dependence plots are drawn as depicted in the figure above. Partial dependence on GNI per capita and life expectancy seems to have a negative relationship with residuals. Higher residuals are partially associated with low national income per capita and life expectancy at birth.

Appendix G. Theory of Change



A large number of hypotheses and indicators found in much CLD programming seem to explore the reaches of program impact rather than reflecting a clearly articulated logic of intervention. Despite a lack of a solid theoretical ground guiding community-driven development, common themes arise in many CLD projects. The figure below delineates a common logic of CLD intervention.

The immediate output of the project would affect the quantity and quality of local public infrastructure and services. As an immediate outcome, there would be more market activity in target communities as well as increases in public infrastructures and services. The intermediate outcome is the changes in household incomes and consumptions in target communities. Program impact includes *social capital/social coherence/conflict management, and local governance* effects. In the long run, the program aims to build capacity of the community to initiate and demand development actions while promoting capacity of the government to supply and respond to the demand. The p*ro-poor orientation* of the project can be considered as a cross-cutting issue. The extent to which benefits accrue to marginalized groups represents central assumptions behind community-driven Development (CLD); that is a demand-driven project enhances the empowerment of the poor (Rao & Ibáñez, 2005).

Taking an example of an irrigation subproject, activity-level measures pay attention to the collective *process* of irrigation infrastructure building. Immediate output indicators reflect the active *use* of this new system. Outcome measures investigate the *change* in crop production and resulting household income. The impact measures consider self-help approach of the project spill over into other realms of village life.

Appendix H. Findings on Key Outcomes from Eleven Impact Evaluations

Country	Name of Project	Funder	Implem-entation	Authors	Year	Study Design	Output		Outcomes
							Services & Infrastructure	Economic & Market	Social capital & Governance
Columbia	PDPMM Generasi	WB, EU	Government	D'Exelle et al.	2018	RCT			+
Afghanistan	NSP	WB	Government	Beath et al.	2013	RCT	+	•	+
DRC	Tuungane	DFID	NGO	Humphreys at al.	2012	RCT	•	•	•
Sierra Leone	GoBifo	WB	Government	Casey et al.	2011	RCT	+	+	•
Indonesia	PNPM Generasi	WB	Government	Olken et al.	2011	RCT	+	N/A	N/A
Liberia	CDR	DFID	NGO	Fearon et al.	2009	RCT	+	•	+
Nepal	Poverty Alleviation Fund	WB	Government	Parajuli et al.	2012	Phase-in RCT DID, IV	+	+	•
Philippines	KALAHI-CIDSS	WB	Government	Edillon et al.	2011	DID PSM	+	+	+
Philippines	KALAHI-CIDSS	WB	Government	Labonne & Chase	2010	DID PSM	N/A	N/A	•
Indonesia, Aceh	BRA-KDP	WB	Government	Barron et al.	2009	PSM IV	•	+	-
Indonesia	KDP (Kecamantan)	WB	Government	Voss	2008	PSM DID	+	+	•

Appendix I. Comparison of Social Capital Dimensions across Studies

Dimensions of social capital	Labonne & Chase (2011)	Grootaert et al.(2003)	Wong (2011)
Group, Network (horizontal or vertical)	• NGO membership • Aware assembly • participate assembly • Know income • Solution assembly • Decision assembly • Service from the local government	• Density of membership • Scope of the group • Internal diversity of organization	• Density of network • Involvement in associations
Information and knowledge	• Supply for collective action • Time spent	• Personal and impersonal source of information • Access to information and communication	
Collective action	• Neighborhood trust • Officials trust • Strangers trust	• The extent of collective action • The type of collective activities • The extent of willingness to participate in collective action	How each individual work together to solve collective action problems
Trust (group, community or institutional level)	• Cohesive network • Perception on village cohesion	• General trust and solidarity • Specific trust and solidarity	Trust towards other members of the community in terms of decision making and the delivery of services
Social cohesion & inclusion		• General perception of social unity • Special experience of exclusion	
Empowerment and political action		• Ability to make decisions • Number of political activities	

Notes: A summary of key dimensions across three development-related studies is presented above. The general commonality among researchers reveals that the concept of "social capital" has been systematized to include a few standardized sub-constructs. "Collective action" and "trust" are the two most common dimensions appearing in all three studies. In addition, scholars generally examine other proxy indicators - group/network, information/knowledge and inclusion. Grootaert et al. (2003) is the only paper that specifies the conceptual theme of each construct. Definitions in two other studies emphasize "collective action," which is considered critical for administering a development project. Labonne and Chase (2005)'s notion of social capital is "the ease with which community members act collectively. Similarly, the World Bank defines social capital as "the norms and networks that enable collective action" (Wong, 2012). Although several other definitions exist, there is consensus to make generalizations about social capital from Putnam (trust, reciprocity, and network) and from Coleman (information, public good, organization).

Appendix J. Correlation among Wealth-Related Measures

Pearson	wealth	night15	night16	share of poor quintiles	rural	Population 15	Population density 15	aridity	borders	water
wealth	1									
night 2015	0.48	1								
night 2016	0.4617	**0.9742**	1							
Share of poor quintiles	**-0.8811**	-0.3351	-0.3261	1						
rural	-0.7298	-0.4809	-0.4498	**0.5772**	1					
population15	0.0557	0.2819	0.313	-0.0353	0.0893	1				
population density15	0.4609	**0.8857**	**0.8927**	-0.3259	-0.4713	0.2974	1			
aridity	-0.1759	-0.0935	-0.0879	0.2277	0.0188	-0.0457	-0.0377	1		
borders	0.1044	-0.0034	-0.0177	-0.1431	0.0561	0.0283	-0.0639	**-0.7245**	1	
water	0.0106	-0.0971	-0.0941	-0.0449	0.0074	-0.0971	-0.1202	0.044	-0.1285	1

Spearman	wealth	night15	night16	share of poor quintiles	rural	population 15	population density 15	aridity	borders	water
wealth	1									
night15	**0.6439**	1								
night16	**0.6672**	**0.8889**	1							
share of poor quintiles	**-0.9405**	-0.5839	**-0.6179**	1						
rural	**-0.6917**	-0.5874	**-0.6165**	**0.6546**	1					
population15	0.0024	0.4078	0.2819	0.0343	0.2651	1				
population density15	0.5696	0.8506	**0.7611**	-0.5137	**-0.6115**	0.536	1			
aridity	-0.1845	-0.2294	-0.1536	0.1855	0.0031	-0.0544	-0.0714	1		
borders	0.0687	0.1501	0.0702	-0.056	0.0822	0.0648	0.0169	**-0.8187**	1	
water	0.0431	-0.1001	-0.0278	-0.048	0.0025	-0.1994	-0.1355	-0.0228	-0.0557	1

Notes: Nightlight 2015 and 2016: 10 km by 10 km resolution

Appendix K. OLS estimates Using Different Nightlights Variables

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
wealth	-191.9*	-187.9*	-219.8**	-498.5***	-490.4***	-539.8***	-352.6***	-354.5***
	(-2.28)	(-2.24)	(-2.62)	(-3.53)	(-3.72)	(-4.51)	(-3.47)	(-3.41)
night5	91.76***							
	(3.93)							
ln_pop	325.8***	328.8***	322.4***	276.4**	269.8***	231.6**	314.9***	310.5***
	(5.31)	(5.38)	(5.36)	(3.33)	(3.48)	(3.00)	(5.19)	(5.05)
borders	-0.00228	-0.00226	-0.00224	-0.00574**	-0.00498**	-0.00508***	-0.00314*	-0.00323*
	(-1.61)	(-1.59)	(-1.59)	(-3.28)	(-3.07)	(-3.46)	(-2.26)	(-2.32)
water	-0.0082***	-0.0082***	-0.0081***	-0.0086***	-0.0088***	-0.0090***	-0.0083***	-0.0083***
	(-9.53)	(-9.50)	(-9.48)	(-6.85)	(-7.47)	(-8.97)	(-9.66)	(-9.73)
aridity	-0.0804***	-0.0804***	-0.0802***	-0.0972***	-0.0923***	-0.0953***	-0.0861***	-0.0858***
	(-6.59)	(-6.59)	(-6.62)	(-5.95)	(-6.12)	(-7.21)	(-7.15)	(-7.11)
night16		96.58***						
		(3.93)						
night15			113.4***					
			(4.56)					
ln_night55				231.7***				
				(4.14)				
ln_night16					227.4***			
					(4.55)			
ln_night15						236.4***		
						(5.21)		
imputed ln low16							142.3***	
							(4.58)	
Imputed ln high 16								147.8***
								(4.40)
Constant	3097.2***	3055.8***	3180.4***	5872.9***	5820.3***	6496.0***	4496.7***	4559.2***
	(4.06)	(4.02)	(4.23)	(4.70)	(4.96)	(5.66)	(5.04)	(4.98)
Observations	441	441	441	238	277	357	441	441
Adjusted R-squared	0.377	0.377	0.385	0.402	0.391	0.403	0.385	0.383

Notes: This table report OLS estimates of weighted aid counts per area using different nightlights variables. * p<0.05, ** p<0.01, *** p<0.001, Standard errors in parentheses, I change years of nightlights (2015 vs 2016), resolutions (High: 5km by 5 km; Low 10km by 10km; or Mix 10 km by 10 km for rural and 2 km by 2km for urban), transformation methods (no transformation vs log transformation with or without replacing 0 with 0.01)

Appendix L. Comparison of Zero vs. Non-Zero Nightlights Villages

Zero-Night villages

Aid Density within 2 ° radius	(1)	(2)	(3)	(4)
wealth index	-127.8	-82.29	-167.7	-104.2
	(219.80)	(230.60)	(203.40)	(212.90)
log of population		95.53		132.6
		(141.50)		(131.50)
proximity to the water body			-0.00496**	-0.00493**
			(0.00)	(0.00)
aridity			-0.0498*	-0.0525*
			(0.02)	(0.02)
constant	2722.9***	1748	4491.9***	3183.6*
	(508.40)	(1531.40)	(655.10)	(1453.70)
Observations	84	84	84	84
Adjusted R-squared	-0.008	-0.015	0.14	0.14

Notes: This table report OLS estimates of weighted aid counts per area. * $p<0.05$, ** $p<0.01$, *** $p<0.001$, Standard errors in parentheses

Non-zero-Night villages

Aid Density within 2° radius	(1)	(2)	(3)	(4)	(5)	(6)
wealth index	-125.9		-336.6**	-472.7***	-367.9***	-509.1***
	(104.40)		(118.30)	(96.19)	(101.80)	(121.30)
night15		136.4***	148.1***	164.5***	133.7***	
		(25.29)	(30.47)	(24.03)	(26.03)	
log of population			346.3***		224.7**	219.8**
			(89.57)		(77.36)	(78.26)
proximity to the water body				-0.00937***	-0.00889***	-0.00868***
				(0.00)	(0.00)	(0.00)
aridity				-0.0651***	-0.0649***	-0.0620***
				(0.01)	(0.01)	(0.01)
log of nightlights						230.0***
						(46.00)
constant	4103.4***	3490.7***	856.3	7134.6***	4410.2***	5536.4***
	(341.50)	(108.10)	(1116.30)	(348.30)	(999.20)	(1130.40)
Observations	357	357	357	357	357	357
Adjusted R-squared	0.001	0.073	0.155	0.374	0.386	0.384

Notes: This table report OLS estimates of weighted aid counts per area. * p<0.05, ** p<0.01, *** p<0.001, Standard errors in parentheses