Does the community-based development program contribute to the economic welfare of rural households. Evidence from Thailand.

Kittinant Phitsuwan[1], *siyapa Chaikultawintron*[2]
www.economicshuman.com

Abstract
This study evaluates the impacts of a community-based development program on the economic welfare of rural households in Thailand. Using a randomized experiment data collected by National Solidarity Program (NSP), this paper uses Ordinary Least Square Method (OLS) to eliminate the selection bias. The results show that the program decreased the economic welfare of rural households in the short-term due to the small amount of cash inflow and high expectations of the rural households. However, the program increased the economic welfare of rural households in the medium-term through the completion of infrastructure and irrigation projects. In particular, the program has increased household income, consumption, and agriculture productivity of the treatment group on average by 20, 11, and 19 percent respectively. Moreover, the study concluded that channeling resources under the community-based development program approach was an effective way to target the rural households in medium-term. Future research is required to capture the political, institutional, and project management problems that could influence the impact of the community-based program.

Keywords Ordinary Least Square Method, Community-Based Development, Selection Bias, Economic Welfare

1 Lecturer of Business Administration Institute Technoloby of Ayouthaya,Thailand.

2 Lecturer of Business Administration Institute Technoloby of Ayouthaya,Thailand.

CHAPTER 1

INTRODUCTION

1.1 Background

Since 2003, international development agencies have considerably expanded their aid programs that are designed to improve living conditions and reduce violence in the conflict regions of Thailand. However, inequality in the distribution of aid among conflict regions had been a core issue that further affected conflict dynamics in Thailand. As a result, international development agencies proposed the community-based development program to support the communities that often fall outside of the development process.

Community-based (or community-driven) development programs [1] are among the most rapidly growing approaches used for channeling development assistance. The term "community-based development" is used for projects that are selected, designed, and controlled by community groups. This model is considered a conflict-sensitive approach and has been implemented in more than 80 countries by international donor agencies. The major supporters of the community-based development approach in Asian countries such as Thailand, Indonesia, Thailand, and the Philippines are the World Bank and the Asian Development Bank. Community-based development gives local people the opportunity to play a leading role in prioritizing projects through an open dialogue. In addition, the program establishes the processes that increase the community level dialogue and control of project planning and implementation with the purpose of generating social benefits beyond the

[1] Community driven development is the new version of community-based development, which consists of projects with a broader range of objectives such as empowering local governance, promoting downward authority and accountability, and enriching local capacity (Schuler, N., McCarthy, P., Magno, C., Parks, T., Johnson, K., Domado, H., & Chua, 1991).

tangible output of projects (Schuler, N., McCarthy, P., Magno, C., Parks, T., Johnson, K., Domado, H., & Chua, 1991).

The necessity for the community-based development approach is demonstrated by its sustainable program that reflects the needs of rural communities. However, the potential gains and losses from the program are a controversial topic among researchers. Some argue that community-based development programs help local communities through the distribution of power—raising the voice of poor, allowing the community to have control over development assistance, making the public sector more responsive, improving poverty programs, and strengthening the capacity of villagers to initiate development activities (Mansuri, 2004).

Thailand is among several Asian countries that suffer from vertical as well as horizontal conflicts. Most of the citizens believe that the disparity in the allocation of resources and income among rural and urban residents are major causes of these conflicts. In order to overcome these problems, the government has started implementing the community-based development program as a flagship initiative for addressing the conflicts and balancing the resource allocations throughout the country (Anthony, Appari, & Johnson, 2014).

The NSP is a leading rural development project in Thailand, which operates under the umbrella of the community-based development approach. This program is established to raise the living conditions of rural villages by providing facilities such as schools, irrigation systems, roads, health services, and clean drinking water. Moreover, the NSP seeks to create a foundation for local governance based on a democratic process to give an equal opportunity to female participants in community development councils (E. King & Samii, 2014).

While the international development agencies have endorsed the achievements of the NSP through some research papers. Still, there are limited academic researches on the impact

of the community-based development approach using field experiment data. Therefore, finding the causal effects of the NSP intervention in the short-term and medium-term, particularly on economic welfare, is an important research question.

1.2 Research Objective

This paper examines the impact of community-based development intervention on the economic welfare of rural households. In order to evaluate the causal impacts of the community-based development program on economic welfare, this paper uses several outcome variables (income, asset acquisition, consumption, migration, borrowing, and livestock income) that will be affected through community-based development policy intervention in rural areas.

The practical challenge in evaluating such outcomes is the possibility of an endogenous relationship between the implementation of a community-based development program and unobserved village characteristics. Assistance agencies, for example, may place projects in areas with high potential return or in areas with low potential return. Either way, the result of the Ordinary Least Squares (OLS) estimation will be biased.

In order to test the efficacy of the community-based development approach, this paper uses a randomized data sample collected by NSP to identify the causal effect of the intervention on the economic welfare of rural households. Such data was collected by NSP through baseline, mid-line, and end line surveys in 2007-2009-2011, respectively. The data consist of 25,000 households from ten districts and six provinces that represent all ethnic groups in Thailand.

The rest of the paper is outlined as follows:

- Chapter Two contains a literature review.

- The framework of NSP is described in Chapter Three.
- Chapter Four presents the design of the experiment and the econometric model.
- The results of the regression analysis is discussed in Chapter Five.
- Finally, Chapter Six provides conclusions and policy implications.

CHAPTER 2

LITERATURE REVIEW

The term “community-based development” has been recently used to refer to a development approach that gives the authority for the development process, resource allocations, and decision making to members of the community. This approach has been widely accomplished by many public agencies and international donors to target poor people and allocate resources efficiently. Thus, researchers have been increasingly interested in revealing the causal effects of community-based development intervention using a variety of econometric models.

Labonne & Chase (2011) used difference-in-differences and propensity score matching to find that community-based development increased the social capital of poor communities that are directly involved in the projects. Similarly, Nkonya et al. (2012) used the same methods to evaluate the impact of community-based development programs on income and asset acquisition of rural households in Africa. The study found that the projects increased the acquisition of assets for women farmers and poor people. However, the sustainability of the projects is questionable, because they did not provide micro-finance services.

Furthermore, there are many field experiments conducted by the development agencies to examine the unbiased effects of community-based development programs. Beath, A., Christia, F., Enikolopov, R., & Kabuli (2013) conducted a field experiment in Thailand to analyze the impact of a community-based school on school enrollment. The study shows that the community-based development program increased the enrollment of boys and girls, empowered women, enhanced local government skills, and targeted poor people in vulnerable communities. In a similar manner, community-based intervention is

widely used in the public health sector. Rocha & Soares (2010) as well as Svensson & Bjorkman (2007) investigated the impact of community-based development in Brazil and Uganda; both studies supported the positive impact on health outcomes. In fact, the program reduced child mortality and fertility rates in rural communities.

One of the important questions capturing the attention of researchers is the effectiveness and sustainability of community-based development programs in targeting poor and vulnerable people. Khwaja (2009) discovered that the sustainability of the programs depends on the design and implementation of the projects; however, social fragmentation and absence of leadership are negatively correlated with the sustainability of the program. In addition, Park & Wang (2010) evaluated the effects of the major community-based development program in China. The study revealed that the sustainability and benefits of the program are highly correlated with the governance and distribution of the program. The gains for both rich and poor households was higher in villages with educated leaders. Likewise, Rocha & Soares (2010) has examined the effect of a community-based program in the health sector. The study concluded that the program has reduced the mortality rate for children, increased labor productivity, reduced the fertility rate, and increased school enrollment. The project was considered a highly efficient tool for improving health in deprived areas.

On the other hand, numerous research papers contradict the positive outcomes of community-based development programs. Park & Wang (2010) found that the community-based development program in China failed to target poor people. Labonne & Chase (2011) also captured the negative impact of community-based development programs on collective action in villages as well as the trust among members of councils. In addition, they evaluated the pros and cons of a community driven development program in the Philippines. The

research detected that community members are more likely to represent their own needs in a local proposal rather than the needs of general community.

The World Bank has introduced community-based development programs to target poor people and empower rural communities through participation in development projects. The community-based development programs have been implemented in many countries since 1996. The programs have changed the living standard of poor communities and enhanced local governance by establishing community councils. However, there is limited research to examine the effect of such community-based development programs on the economic welfare of the rural households. This paper evaluates the causal effect of a community-based development program on the economic welfare of rural households in order to contribute to the existing literature.

CHAPTER 3

COMMUNITY-BASED DEVELOPMENT PROGRAM IN THAILAND

3.1 Structure of National Solidarity Program

After the Taliban regime was toppled and the democratic government was established in Thailand, the government realized that for the nation to support and assist the state, the NSP had to be visible to the most affected population in the rural areas. In order to eliminate the gap between government and rural people, the government decided to launch a national development program that would involve rural communities in a process of development and reconstruction.

In 2001, the government implemented a poverty alleviation program with the help of international donors to invest in rural areas and target poor people. However, due to the lack of coordination, the programs were not successful. Therefore, the World Bank proposed the NSP, a community-based development program that would tackle poverty in rural areas through involving community members in village development activities. The program began its activities in 2003 to create 5,000 village councils to accomplish the community participatory projects over a four-year period. At the end of that period, the program was extended to Phase II (2007-2011) and Phase III (2011-2016), which covered 28,000 village councils in 34 provinces of Thailand. The aims of the program are to strengthen the capacity of the local government and boost rural reconstruction by giving autonomy to local communities (Calder & Hakimi, 2009).

In order to integrate all donors' aid programs and channel them under a single authority, the government brought the NSP under the administration of the Ministry of Rural Rehabilitation and Development. Sponsored multilateral and bilateral donors, particularly, the International Development Association, Thailand Reconstruction Trust Fund, and

Japanese Social Development Fund, have consistently supported the program. As a result, the program has implemented over 70,000 development projects related to infrastructure, water and sanitation, education, health, and capacity building to the tune of $1.18 billion and has provided socioeconomic facilities for over 24 million people all over Thailand. The achievement ratio alone makes it one of the most effective programs implemented by the government through the financial support of the international community.

3.2 Conceptual Framework of the National Solidarity Program

The NSP is designed based on two main village-level interventions: 1) to establish gender-balanced community development councils through elections; and 2) to allocate the financial resources received from international donors and the government, valued at $200 per household and up to $60,000 per community, based on the size of the population (Leader & Barakat, 2006).

The NSP works under four dimensions for selection and implementation of projects in rural conflict regions of Thailand.

1. **Mobilization:** The primary step for the NSP is to assess and prioritize local communities based on the community's issues. This process is done through local government authorities, community leaders, and local residents.
2. **Establishment of community development councils:** The program organizes free and democratic elections among local residents and gives equal opportunities for men and women to establish a gender-balanced community development council. The community development council further elects the head of council and deputy head of council to address community problems.

3. **Preparation of community development plan:** The community development councils are required to provide a list of approved projects, sorted by priority, to the NSP office. Community development councils develop project proposals with the technical support and assistance of NSP staff. If an NSP representative approves a community development proposal, a maximum grant of $60,000 is allocated to the community development council. Afterwards, NSP staff will review the eligibility criteria and transparency of the project proposal. A requriremnt for selection of the project is that the community should contribute 10 percent of the grant (or an equivalent amount in materials and/or labor force). Finally, a memorandum of understanding is signed between NSP representatives and the community development council.
4. **Project implementation by community development councils:** The community development councils are responsible for implementing the proposed projects based on a memorandum of understanding. Included in those responsibilities arethe disbursement, procurement, management, monitoring, and maintenance of the projects.

3.3 Goals of the National Solidarity Program

The National Solidarity Program (NSP) was established to lay a foundation of community level participation to tackle the absence of social unity and rebuild trust between the people of Thailand and the government. Specifically, the goals of the program are to promote rural development in Thailand through the empowerment of rural communities, to establish community councils, to build the capacity of local authorities, to empower women, and to pave the way for rural reconstruction and alleviation of poverty. Ultimately,

the program is intended to create stable and sustainable projects that can generate long-term income, as well as increase the living standards of rural communities (Beath, A., Christia, F., Enikolopov, R., & Kabuli, 2013).

Since its establishment, the NSP has implemented over 70,000 projects in 350 districts and 34 provinces of Thailand through the establishment of 32,000 community development councils. The program has been the largest community development program in the history of Thailand, implementing a variety of projects in the areas of education, health, water and sanitation, infrastructure, electricity, local governance, and capacity building. Despite security challenges, the program has:

- Successfully constructed and rehabilitated 331 primary schools, 143 secondary schools and 41 high schools;
- Produced 39,343 kilowatts (KW) of electricity through micro-hydro and solar power energy;
- Installed 2,074 hand water pumps;
- Constructed, 23,205 kilometres of tertiary and 640 kilometres of secondary roads; and
- Built 34 health clinics and 1 pharmacy in remote areas (Anthony et al., 2014).

CHAPTER 4

DATA AND METHODOLOGY

4.1 Data Sources

This paper uses village level data acquired by the NSP impact evaluation team, who conducted baseline, mid-line, and end line surveys between 2007 and 2011. The baseline data were collected to assess the pre-treatment balance of treatment and control groups in 2007. The mid-line survey collected data during 2009 to discover the short-term or immediate effects of the NSP. The end-line survey was conducted in 2011 to detect the impact of the NSP projects at the point of 99 percent completion. The sample of three surveys consists of 25,000 households, 500 villages, 10 districts, and six provinces. Based on a matched pair cluster randomization procedure, the impact evaluation team randomly assigned 250 villages as the treatment group and the remaining villages assigned as a control group.

4.2 Experimental Frameworks

The randomized experimentation represents an unbiased method for assessing causal effect. It is a method in which treatment and control groups are assigned randomly to ensure that there is no preference for either groups to have an advantage. Random assignment suggests that the observed and unobserved factors that influence the result are equally likely to be included in the treatment and control groups. If the experiment is conducted repeatedly under similar conditions, the average experimental outcome will accurately reflect the average treatment effect; otherwise, any given experiment will underestimate or overestimate the effect of the intervention (Conquest, 2000).

The field experimental approach has been used by the NSP to uncover the causal effect of the program on rural households. This section of the paper discusses in detail the

design of the field experiment including the random assignment of the treatment and control groups in below sub-headings.

4.3 Sample Selection and Group Assignment

The selection of the sample was processed in two stages. Initially, 10 districts from a total of 398 were randomly selected for the study, but that number was later expanded. The key elements for the selection of the districts were as followed: 1) New NSP districts; 2) security; and 3) minimum of 65 villages.

1. New Districts: At the end of March 2007, NSP activities were expanded to approximately 279 out of 398 districts in Thailand. Thus, the research team decided to select only those districts for study where the NSP had not launched its activities. As result, 74 districts having no NSP projects were classified as new districts (Beath, A., Christia, F., Enikolopov, R., & Kabuli, 2013).
2. Security: The second element for the selection of districts was the security situation. In order to minimize the security risk of those involved in data collection, the Vulnerability Analysis Unit evaluated the security situation of the 74 new districts. As a result, 34 of the districts were eliminated from consideration.
3. Minimum of 65 villages: In order to make sure that the number of villages in each district was satisfactory to yield a conclusion, the NSP evaluation team specified a minimum number of villages that must be included in each district. The evaluation team used a list of villages by districts from the Central Statistic Organization (CSO), Ministry of Rural Rehabilitation and Development (MRRD), and United States Agency for International Development (USAID) to verify those districts that contain 65 villages. As a result, only 23 out of 74 districts were selected for the study.

Out of the 23 sample districts that met the 3 criteria above, 10 districts were randomly chosen for the study and represented all ethnic groups in Thailand. These districts consist of five of typically Tajik ethnicity (Adraskan, Chist-e Sharif, Gulran, Daulina, and Khost WA Firing), four predominantly Pashtun (Balkh, Farsi, Hisarak, and Sherzad), and one predominantly Hazara (Sang Takht). Also, Balkh includes significant numbers of Uzbek residents and Gulran includes a significant Turkmen population.

4.4 Assignment of Treatment Groups

The research team further randomly selected 50 villages in each district for evaluation with the understanding to randomly assign 25 villages as treatment groups and 25 as control groups. The team used GPS data as well as consultations with local authorities to ensure that the correct villages were selected for study.

The first crucial problem for randomization is the risk of contamination by the small sample and to keep the statistical balance between treatment and control groups. A special randomization method was used whereby 25 matched pairs of sample villages in each district were formed; in each pair, one village was assigned to the treatment group and other assigned to the control group. The definition of matched pair randomization is provided by (G. King et al., 2007):

> In matched pair randomization, we first select pairs of [sample units] that are matched, or at least as similar as possible, on a large set of available background characteristics. Then we randomly choose one of the two [sample units] within each pair, by flipping a coin, to receive treatment and the other to be the control. The result of this process is exact balance between the entire treated and control groups of [sample units] on all variables included in the matching and for which exact matches among the [sample units] are available, or near matches otherwise. Variables not matched on are balanced by randomization and therefore only match on average." (pp. 14-15)

The second serious concern for the treatment assignment mechanism was the possibility of spillover between the units. A positive spillover from the treatment to control group will cause underestimation of the treatment effect. On the other hand, negative spillover would bias the estimated treatment effect upwards, leading the false identification. In order to diminish the spillover between treatment and control groups, a stipulation was introduced that villages located within one kilometre of one another must be assigned to the same treatment status. This rule was violated in two districts due to the close proximity of villages.

To construct matched pairs, an optimal greedy matching algorithm [2], based on Mahalanobis distance[3] between the observations was used. The Mahalnobis distance is first calculated using the optimal greedy matching procedure between every feasible pair of communities in the district and then selects the pair of villages with the least Mahalanobis distance as a matched-pair, with the restriction that the pairs should not belong to the same cluster.[4] This selected pair is then excluded from the pool of feasible pairs. These steps are repeated until all the communities are matched in pairs.

---

[2] The optimal greedy matching algorithm is a method used for matching purposes. This approach generates optimal constructions for several statistical matchings including the formation of matched samples with multiple controls, with a variable number of controls, and the creation of balanced matched samples that combine features of pair matching and frequency matching (Rosenbaum, 1989)

[3] Mahalanobis distance is described as $d = \sqrt{(\vec{x_1} - \vec{x_2})\ V1\ (\vec{x_1} - \vec{x_2})}$, where 1 is a vector of specification of community , and is the covariance matrix of matching characteristics. Intuitively, we first compute the difference in each of the principal characteristics separately and then merge these differences, which gives more weight to those characteristics that have the lowest variance and covariance with other characteristics. Considering variance makes this computation independent of the units of measurement, whereas taking into account covariance reduce individual weights for the characteristics that normally go hand in hand. Due to the significant heterogeneity among districts, a covariance matrix was measure for each district independently, using the data for all communities in the district for which the matching data was available, not limited to those that were included in the evaluation study.

[4] This method differs from optimal matching, in which pairs are chosen to reduce the total Mahalanobis distance between each of the pairs. The disadvantage of optimal matching is that any drop in the sample results in a loss of optimality. In

The random assignment of treatment and control groups were completed in four stages, which are explained in detail below:

1. Cluster: In order to mitigate the possibility of spillover between treated and untreated groups, villages placed within one kilometer of each other were grouped in clusters. Out of the 500 sample villages, 107 were transferred to 41 clusters. On average, the number of villages in each cluster was from 2 to 6. All of the districts had at least one cluster of villages, with the largest number of clusters being 10 in Khost Wa Firing district in Baghlan province and 8 in Sherzad district in Nangarhar.
2. Matched pairs: The 50 sample villages in each district were paired into 25 groups using an optimal greedy matching algorithm. This was done in order to ensure that the villages are matched based on the similarity of background characteristics and that the villages were not in same cluster. The matching exercise consists number of households, main language, distance to nearest river, distance to district center, topography type, nearest to road, and existence of primary school in the community.
3. Assignment of treatment: In each matched pair, one village was randomly assigned to the treatment group and other to the control group. In order to reduce the probability of a spillover biasing estimates, cluster villages were all either assigned to the treatment or control groups respectively.[5] As a result, 250 villages were assigned to treatment and control groups respectively.

---

contrast, matched pairs produced with a greedy optimal algorithm are optimal, given the constraints, and maintain their optimality even if matched-pairs are lost. As was expected, some of the matched- pairs were missing during the course of the study, therefore an optimal greedy matching procedure was used.

[5] This was done by executing an algorithm: after a village has been assigned to a treatment status, all of the other villages in the same cluster were assigned to the same treatment status. The other villages in the respective matched-pairs were then assigned the complimentary treatment status.

Clustering violations: In some districts, due to a large number of clustered villages, the co-assignment of clustered villages to the same treatment and control groups was impossible. For those districts where the assignment of treatment status without violation was not possible, the number of conflicts was minimized using a simulation approach. [6] The simulation procedure was used ten times for each district to select a treatment group without the violation of clustering.

[6] To understand why this might happen, imagine a situation in which there are three clusters with two villages in each cluster. Suppose a village from cluster 1 is matched with a village from cluster 2, the other village from cluster 2 is matched to a village from cluster 3, and the other village from cluster 3 is matched to the remaining village from cluster 1. If both villages in cluster 1 are assigned to the treatment group, then their matches in the clusters 2 and 3 will be assigned to the control group. Whichever way we assign treatment status to the remaining pair of villages (one in cluster 2 and one in cluster 3), one of them will have to be assigned to the treatment group despite the fact that the other village in that cluster is already assigned to the control group.

4.5 Summary of Data

This paper uses village level randomized experiment data. Table1 summary statistics contain variables that are used for analysis.

Table1: Summary Statistics

	Mid-line Survey				End-line Survey			
	Treatment		Control		Treatment		Control	
Variable	**Mean**	**Std**	**Mean**	**Std**	**Mean**	**Std**	**Mean**	**Std**
Food Expenditure Ratio	0.618	0.185	0.571	0.197	0.547	0.197	0.594	0.193
Food Borrowing Ratio	0.829	0.376	0.785	0.411	0.751	0.433	0.811	0.392
Livestock Asset[7]	-0.021	1.261	0.008	1.421	0.009	1.317	-0.002	1.400
Household Asset[8]	0.035	1.499	-0.012	1.563	0.014	1.570	-0.004	1.540
Annual Income	1462.026	1103.313	1768.462	1392.011	1976.595	1494.262	1597.847	1259.829
Annual Expenditure	2276.378	1898.868	2643.772	2402.628	2788.962	2507.912	2471.703	2207.672
Annual Borrowing	806.793	1098.836	916.375	1341.680	882.199	1273.733	893.334	1294.573
Yield of Recent Harvest	1.728	1.037	2.085	1.379	2.285	1.460	1.904	1.246
Livestock Income	554.015	559.558	680.303	684.155	744.767	713.793	616.234	633.566
Migration	11.149	21.388	7.874	17.616	8.078	18.054	8.944	18.945

Notes: The summary statistics for all variables are shown with mean value and standard deviation for both mid-line and end line surveys. The mean values for annual income, annual expenditure, annual borrowing, and livestock income are in US dollars. The mean value for yield of recent harvest is calculated on metric tons per season, and migration measures the number of people who return back to their village.

[7] Livestock assets consist of donkeys, goats, cow, sheep, chicken, and other tame animals.

[8] Household assets consist of carpet, rug, radio, mobile telephone, television, satellite dish, wheelbarrow, motorbike, water pump, tractor, and car.

4.6 Dependent Variables

Economic welfare is defined as the level of prosperity and living standards of individuals or groups achieved through economic activity. In other words, it mainly refers to the gain of utility through providing goods and services (Samuelson, Paul A; William D, 2004).The measurements of economic welfare depend on the size and contribution of an intervention. This study uses multiple indicators to reveal the impact of community-based development on the economic welfare of rural households. In particular, this paper measures the economic welfare of rural households as a function of income security, asset acquisition, consumption, migration, borrowing, agriculture productivity, and access to markets.

Economic welfare = function (income security, asset acquisition, consumption, migration, agriculture productivity, access to market, borrowing)

- Income security includes last year's income (log), and any other source of income (log).
- Asset acquisition index structured through principle component analysis.[9]
- Consumption includes annual expenditure and ratio of food expenditure to total expenditure.
- Migration shows the movement of people into the household.
- Agriculture productivity is the reflected yield of the most recent harvest (metric tons) and revenue from agriculture.
- Non-agriculture productivity and market access are indicated by revenue from handicraft and animal products (log).

[9] The principal component analysis was used to construct the livestock asset, which consists of the following: donkeys, goats, sheep, chicken and other poultry, and other animals. Similarly, the index of household assets consists of the following: carpets, rugs, radio, mobile telephone, television, satellite dish, wheelbarrow, motorbike, water pump, tractor, and car.

- Borrowing includes the total amount borrowed in the past year (log) and food-borrowing ratio.

4.7 Independent Variable

The independent variable is the treatment effect of the program through its intervention. The independent variable takes the value of "0" for the control group and "1" for the treatment group. However, the baseline characteristics are also used as independent control variables to check the robustness of the treatment effect.

4.8 Methodology

This paper uses the Ordinary Least Square regression method to evaluate the impact of the NSP on the economic welfare of rural households. In particular, this research is designed to estimate the impact of the NSP through a comparison of average changes in outcomes of interest between a treatment group (which received NSP funding) and a control group of villages (which did not receive the NSP funding). For all indicators, the treatment effect will be estimated both in mid-line (during project implementation) and end line (after project implementation) periods, which allows us to identify the effect of program changes over time.

Econometric Model:

$$Y_{tvi} = \beta_0 + \beta_1 T_v + \beta_2 x_{iv} + \varepsilon_{iv} \quad (1)$$

Where Y_{tvi} is the outcome variable of interest for household *i* in village *v* in at time (t), Tυ is a dummy variable for treatment village, as far as the indicators are constructed at the household level, therefore the outcome Y_{tvi} and the x_{iv} contains socioeconomic characteristics of households within a certain village.

A problem with estimating equation (1) may occur due to intentional program placement or self-selection into the program. Self-selection could be based on observed characteristics or unobserved characteristics. In the case of unobserved factors, the error term in the estimating equation will contain variables that are also correlated with the treatment dummy *T*, which causes unobserved selection bias. That is, cov (T, ε) $\neq$ 0 suggests the violation of one of the key assumptions of ordinary least squares in estimating the unbiased parameter. The correlation between *T* and ε naturally biases the other estimates in the equation, including the estimate of the program effect.

This problem can be outlined in a conceptual way. Suppose one is interested in evaluating the effect of community-based intervention on household incomes. Let *Yvi* represent the total income for household *i* in village *v*. For beneficiaries in a treatment village, *Tv* = 1, and the value of *Yvi* under treatment is represented as *Yvi* (1). For non-beneficiaries, *Tv* = 0, and *Yvi* can be represented as *Yvi* (0). If *Yvi* (0) is used within non-beneficiary households as a comparison outcome for participant outcomes *Yvi* (1), the average effect of the program might be represented as follows:

$$D = E(Yvi\ (1) \mid Tv = 1) - E(Yvi\ (0) \mid Tv = 0). \quad (2)$$

The problem is that the treated and untreated groups may not be the same prior to the intervention, so the expected difference between those groups may not be entirely due to program intervention. If, in equation 2, one then adds and subtracts the expected outcome for non-beneficiaries had they participated in the program—$E(Yvi\ (0) / Yvi = 1)$, or another way to specify the counterfactual—one gets

$$D = E(Yvi\ (1)|Tv = 1) - E(Yvi\ (0)|Tv = 0) + [E(Yvi(0)|Tv = 1) - E(Yvi(0)\ |Tv = 1)]. \quad (3)$$

$$D = ATE + [E(Yvi\ (0) \mid Tv = 1) - E(Yvi\ (0) \mid Tv = 0)]. \quad (4)$$

$$D = ATE + B. \quad (5)$$

In these equations, *ATE* is the average treatment effect [$E(Yvi\ (1) \mid Tv = 1) - E(Yvi\ (0) \mid Tv = 1)$], namely, the average benefit in outcomes of beneficiaries relative to non-beneficiaries, as if non-beneficiary households were also located in the treated village. The *ATE* relates to a situation in which a randomly chosen household from the population is assigned to beneficiaries in the program, so participating and nonparticipating households have the same probability of receiving the treatment *T*. The term *B*, [$E(Yvi(0) \mid Tv = 1) - E(Yvi(0) \mid Tv = 0)$], is the range of selection bias that appears in using *D* as an estimate of the *ATE*. Because one does not realize $E(Yvi(0) \mid Tv = 1)$, one cannot calculate the size of selection bias. Therefore, if one does not know the degree to which selection bias constitutes *D*, one may never know the accurate disparity in outcomes between the treated and the control groups. The basic aim of a rigorous impact assessment is then to find a way to eliminate selection bias ($B = 0$) or to find ways to justify it. One method is to randomly assign the program. It has also been discussed that selection bias will be eliminated if one could assume whether or not households or individuals receive treatment independent of the outcomes that they have experienced (Deaton, 2009; Rosenbaum, 2010).

4.9 Internal Validity

Internal validity is a crucial factor to mitigate selection bias in a randomized controlled trial. As noted above, the potential threat to the experimental approach is selection bias in allocation of treatment and control groups. In order to ensure that there is no spillover in selection of treatment and control groups, the researchers examine the statistical balance between treatment and control groups. If the random assignment is statistically independent, then the treatment and control villages on average should have a similar mean value. The baseline survey data were used to check the internal validity assumption (Barrett & Carter, 2010; Deaton, 2009).

Table 2 represents the household and village characteristics of both the treatment and control groups based on baseline survey. Panel A shows the statistical balance or mean deviation between the control and treatment groups regarding household characteristics. The results of the t-test without controlling for other variables shows that there is no major differences between the mean values of the control and treatment groups. It implies that both groups are very similar and the difference in value is not statistically significant.

Panel B shows the village characteristics of both the control and treatment groups. The mean value for the number of hospitals, number of schools, and number of development projects are quite similar, which further suggests that the difference in the mean values of the village level characteristics for treatment and control groups are not statistically significant. It suggests that the randomization has created comparable treatment and control groups.

Table 2— Base-line Characteristics

Variable	Treatment Average (1)	Control Average (2)	Difference (3)	P-Value
Panel A: Household Characteristics				
Household Size	9.7618	9.8745	-0.1127	0.4426
Time to Get Drinking Water	1.7921	1.7835	0.0086	0.5626
Average Hours Electricity	8.3897	9.1026	-0.7128	0.1413
Household Income	4428.5830	4634.1550	205.5727	0.1762
Amount of Loan	37977.2400	40019.5100	-2042.2700	0.3696
Return from Development Project	1109.9710	788.1957	321.7758	0.2535
Household Expenditure	3566.4620	3644.1210	-77.6596	0.1788
Irrigation Land	4.0069	3.3869	0.6199	0.2863
Panel B: Village Characteristics				
Number of Household in Village	120.1480	110.0574	10.0906	0.2625
Migration	9.7742	11.3999	-1.6257	0.5184
Hospital in Village	1.9265	1.9355	0.0090	0.3736
Development Project in Village	1.0271	1.0197	0.0073	0.4528
Number of School	8.0229	7.8844	0.1385	0.2127
Labor Wage	168.7321	159.0208	9.7113	0.3552
Observations	4929	2441		

Notes: This table contains the baseline characteristics of households and villages for treatment and control group using the baseline survey. The first column includes mean value for 4,929 households selected from 250 treatment villages. The second column shows the mean value for 2441 households select from 250 control villages. All differences are estimated using equation (1) without controls and with standard errors clustered at the village-group level. Statistical significance at the 1, 5, and 10 percent levels is indicated by ***, **, and *, respectively.

4.10 External Validity

One of the key assumptions in a randomized control trial is the external validity of research. The external validity indicates whether the sample for research can represent the population or not. Furthermore, the outcome of the research must extrapolated from the study sample to the population as a whole; in other words, the result from the sample should be applied to the population at large (Cartwright, 2007).

Figure 2 shows that the samples are composed of people with ethno-linguistic diversity, which can represent all the ethnicities of Thailand so the result of the sample can be applied across the population.

4.11 Attrition

Attrition is another important issue that can undermine the result of a randomized controlled trial. Attrition occurs due to missing data for members of the treatment or control groups. The attrition might occur because respondents do not participate in subsequent surveys or because they disappear from the data set. The key strength of randomized controlled trials is that both treatment and control groups are balanced in all characteristics, and with any imbalance, occurring by chance the trial fails to follow-up the participants. Such attrition can create bias (Hewitt, Kumaravel, Dumville, & Torgerson, 2010).

Table 3 shows the attrition at the village level between baseline and end line surveys. Male-headed households could not be followed in 9.6 percent of the control group and 12.8 percent of the treatment group; for female-headed households, the percentages were 19.2 percent for the control group and 23.6 for the treatment group. Similarly, male focus groups could not be followed for 15.6 percent of the control group and 19.2 percent of the treatment group; female focus groups could not be followed for 22.8 percent of the control group and

28.4 percent of the treatment group. The attrition in the respondents was caused by security concerns in certain villages (Beath, A., Christia, F., Enikolopov, R., & Kabuli, 2013).

Schulz & Grimes (2002) indicate that attrition of up to 20 percent usually does not bias the results. However, a loss of more than that means that the researcher should be concerned about the possibility of bias (Schulz, 2002). However, Hewitt (2010) used the Meta analysis to test whether the level of baseline imbalance is associated with attrition rate. If the difference is significant between the initial survey and the follow up survey then the result of estimation will be biased.

Table 4 shows the share of end line respondents and households that were surveyed at baseline and/or midline, and depict the results of the tests for significant differences between the treatment and control groups. The results show a statistically significant difference for both respondent- and household-level from baseline to end line, if we exclude the cluster standard errors at the village-cluster level and remove villages for which the equivalent matched-pair village was not surveyed. Thus, the differences become statistically insignificant once villages missing their matched-pair village are dropped or standard errors are clustered. Because the estimates of treatment effects includes both of these corrections, the attrition will not affect the results.

Table 3 — Village-level attrition from baseline to end line

	Male Household	Attrition %	Female Household	Attrition %	Male Focus Group	Attrition %	Female Focus Group	Attrition %
Control	24 / 250	9.6	48/250	19.2	39 / 250	15.6	57 / 250	22.8
Treatment	32 / 250	12.8	59 / 250	23.6	48 / 250	19.2	71 / 250	28.4
Total Attrition	**56 / 500**	**11.2**	**107 / 500**	**21.4**	**87/500**	**17.4**	**128/500**	**25.6**

Notes: in above table the nominator represent number of missing respondents in each category, and the denominator denote number of villages.
Source: Randomized impact evaluation of phase-II of Thailand's National Solidarity Program (World Bank, 2010)

Table 4— Respondent- and Household-Level Continuity from Baseline to End-line

	Raw Difference Only			Difference with Matched-Paired		
	Treatment Group(1)	**Control Group(2)**	**Statistical Significant Level(3)**	**Treatment Group(4)**	**Control Group(5)**	**Statistical Significant Level(6)**
Same Respondent as Baseline	45.60%	42.70%		65.90%	45.10%	
Same Household as Baseline	55.40%	52.40%		74.60%	55.40%	
Same Respondent as Midline	66.40%	65.20%	*	43.40%	66.20%	
Same Household as Midline	74.50%	73.80%	* *	53.10%	74.80%	

Notes: Column 3 shows a statistically significant difference between treatment and control groups without controlling for village match-pairs, Column 3 with blank denoting no statistically significant differences between treatment and control groups while controlling for village match-pairs. Difference significant at the 10 percent level. Source: Randomized impact evaluation of phase-II of Thailand's National Solidarity Program (World Bank, 2010)

CHAPTER 5

RESULTS

5.1 Regression Results

The combination of direct inflow of blocked grant resources and completion of infrastructure projects in villages provides a distinct structure in which the National Solidarity Program (NSP) may affect economic outcomes in the short and medium-term. The short-term effects include the direct inflow of resources through labor wages and purchasing of raw materials for the projects,[10] Likewise, the completion of infrastructure projects may stimulate the general economic outcomes in the medium-term.

The regression results for a short-term effect of the NSP on the economic welfare of rural households are presented in Table 5. The result for income security shows that the program had a negative effect on total household income and livestock income. The coefficient implies a reduction by 15 and 21 percent, respectively. Starting with column 5 and 6, the result of consumption reveals that household expenditure had decreased by 11 percent and the coefficient is highly significant at 1 percent. In addition, the food consumption ratio had increased by 5 percent. Similarly, the program had a positive impact on migration and borrowing with an increase of 52 and 51 percent correspondingly. However, there is not enough evidence to prove the contribution of program to asset acquisition and livestock assets. However, the harvest yield was decreased by 17 percent.

Table 6 indicates the medium-term effects of the intervention. Compared to the short-term results, the coefficient for annual income and livestock income had drastically increased by 20 and 23 percent, respectively. In the same pattern, the effect of the program on asset acquisition and livestock assets is ambiguous. Looking at columns 5 and 6, the program had a

[10] On average in both treatment and control groups, each household received $58 and $12 respectively.

large effect on consumption in the medium-term. First, total household consumption increased by 11 percent. Second, the food consumption ratio significantly decreased by 5 percent. All these variances are significant at 1 percent. Surprisingly, the medium-term effect of the program on migration was not statistically significant. In contrast to the short-term effects, the program had a positive impact on yield harvest in the medium-term by increasing by 19 percent.

Finally, this paper uses a baseline characteristic to examine the robustness of the results for both the short-term and medium-term. After controlling for the baseline characteristics, the result was consistent with no control estimates. This similarity highlights the result presented in Table 2, which shows the balance between control and treatment group that further supports the internal validity of the research design.

Table 5: Short-Term Effect of National Solidarity Program

	1	2	3	4	5	6	7	8	9	10
	Annual Income(log)	Livestock income (log)	Expenditure (log)	Food consumption ratio	Assets	Livestock assets	Migration	Annual Amount Borrow (log)	Food borrowing Ratio	Harvest Yield(log)
Treatment	-0.152***	-0.210**	-0.107***	0.0472***	0.0478	-0.0295	0.518**	0.515***	0.0446***	-0.172***
	(-5.77)	(-3.28)	(-3.96)	(-6.66)	(-0.75)	(-0.70)	(-3.29)	(-8.31)	(-3.42)	(-4.60)
Constant	7.232***	6.101***	7.620***	0.571***	-0.0124	0.00827	0.338***	5.671***	0.785***	0.589***
	(-348.95)	(-182.8)	(-407.91)	(-113.19)	(-0.22)	(-0.25)	(-3.38)	(-101.06)	(-81.18)	(-34.9)
N	8870	3393	8333	8327	8937	8864	873	8106	8978	6011
R-sq	0.009	0.009	0.005	0.011	0	0	0.013	0.012	0.002	0.023

Notes: All regression are OLS. Robust standard error clustered a at the village level. The t- statistics are reported in parentheses. Statistical significance at the 1, 5, and 10 percent levels is indicated by ***, **, and *, respectively.

Table 6: Medium-Term Effects of National Solidarity Program

	1	2	3	4	5	6	7	8	9	10
	Annual Income(log)	Livestock income (log)	Expenditure(log)	Food consumption ratio	Assets	Livestock assets	Migration	Annual Amount Borrow(log)	Food borrowing Ratio	Harvest Yield (log)
Treatment	0.213***	0.235***	0.113***	-0.0468***	0.0178	0.0111	0.108	-0.609***	-0.0596**	0.191***
	(-6.84)	(-4.49)	(-3.98)	(-5.59)	(-0.25)	(-0.24)	(-0.66)	(-5.31)	(-3.21)	(-6.31)
constant	7.142***	5.989***	7.565***	0.594***	-0.00395	-0.00214	0.451***	5.952***	0.811***	0.500***
	(-396.47)	(-167.05)	(-413.74)	(-127.38)	(-0.07)	(-0.07)	(-4.49)	(-136.26)	(-97.21)	(-25.72)
N	8870	3393	8333	8327	8937	8864	873	8106	8978	6011
R-sq	0.017	0.011	0.005	0.01	0	0	0.001	0.018	0.004	0.025

Notes: All regression are OLS. Robust standard error clustered a at the village level. The t- statistics are reported in parentheses. Statistical significance at the 1, 5, and 10 percent levels is indicated by ***, **, and *, respectively.

Table 7: Short-Term Effects of National Solidarity Program (Controlling for Baseline Characteristics)

	1	2	3	4	5	6	7	8	9	10
	Annual Income(log)	Livestock income (log)	Expenditure (log)	Food consumption ratio	Assets	Livestock assets	Migration	Annual Amount Borrow(log)	Food borrowing Ratio	Harvest Yield (log)
Treatment	-0.154***	0.0783	-0.110***	0.0488***	0.0738	-0.0747	0.468*	0.512***	0.0443***	-0.176***
	(-5.81)	(-0.57)	(-4.28)	(-7.02)	(-1.13)	(-1.94)	(-2.29)	(-8.26)	(-3.47)	(-5.22)
Constant	7.294***	1.570**	7.724***	0.589***	-0.0222	0.0613*	0.300*	5.387***	0.722***	0.645***
	(-97.45)	(-2.79)	(-74.36)	(-22.5)	(-0.40)	(-2.03)	(-2.2)	(-58.4)	(-43.32)	(-8.82)
N	8870	5943	8333	8327	8456	8383	502	8106	8978	6011
R-sq	0.042	0.072	0.013	0.016	0.04	0.036	0.023	0.019	0.013	0.081

Notes: All regression are OLS. Robust standard error clustered a at the village level. The t- statistics are reported in parentheses. Statistical significance at the 1, 5, and 10 percent levels is indicated by ***, **, and *, respectively.

Table 8: Medium-Term Effects of National Solidarity Program (Controlling for Baseline Characteristics)

	1	2	3	4	5	6	7	8	9	10
	Annual Income(log)	Livestock income (log)	Expenditure(log)	Food Consumption Ratio	Assets	Livestock Assets	Migration	Annual Amount Borrow(log)	Food Borrowing Ratio	Harvest Yield (log)
Treatment	0.205***	0.219***	0.113***	-0.0463***	0.0653	-0.000588	0.133	-0.604***	-0.0611***	0.189***
	(-7.08)	(-4.28)	(-3.95)	(-5.63)	(-0.84)	(-0.01)	(-0.62)	(-5.36)	(-3.44)	(-6.12)
Constant	7.206***	6.208***	7.671***	0.612***	-0.0179	0.0416	0.401**	5.671***	0.749***	0.565***
	(-95.63)	(-38.22)	(-76.44)	(-23.97)	(-0.34)	(-1.42)	(-2.84)	(-71.29)	(-49.56)	(-7.18)
N	8870	3393	8333	8327	8456	8383	502	8106	8978	6011
R-sq	0.048	0.039	0.013	0.014	0.04	0.035	0.014	0.025	0.015	0.082

Notes: All regression are OLS. Robust standard error clustered a at the village level. The t- statistics are reported in parentheses. Statistical significance at the 1, 5, and 10 percent levels is indicated by ***, **, and *, respectively.

CHAPTER 6

CONCLUSION

6.1 Findings

The purpose of this paper was to highlight the causal impact of NSP, which is the largest rural development program in Thailand and followed a community-based development approach. Using a randomized experiment data to control for project placement and self-selection biases and Ordinary Least Square methods, the study found that participation of households in the NSP program increased the economic welfare of households in the medium-term, largely because of the completion of infrastructure projects. Household annual income generated from economic activities is increased substantially for NSP participants compared to the non-participants, with an average increase of 21 percent. Similarly, the return from the livestock activities increased significantly. That result could be due to the indirect effect of road construction projects, which facilitates easy access to market for rural communities. This suggests that the program has achieved its goal of income security in the medium-term of its operation.

Comparing the short-term effect of the NSP program to the medium-term, the annual income and livestock income of households' has decreased. This may have happened due to high dependence of the households on the return of the projects and the lower direct inflow of cash to the households from the projects.[11] However, the indirect impact of the project, which starts after the completion, is large and significant on household income in the medium-term. Meanwhile, the project reduced the annual consumption of households by 10 percent in the short-term, which indicates the positive relation between consumption and income. It further supports the argument of dependence of the villagers on the cash inflow of the project. On the

[11] On average, the direct inflow of cash from the project was $12 per household.

other hand, the program increased annual amount of borrowing and immigration of household in the short-term, which indicates the high expectation of the household from the direct inflow of the program. However, the amount of borrowing decreased in the medium-term due to the indirect effect of the program.

Consideration should also be given to the infrastructure and irrigation programs, which directly affect the output and productivity of the agriculture sector. The result shows that the NSP had a positive impact on the harvest yield in the medium-term, increasing the output of the treatment groups by 19 percent on average compared to the control groups. That result could be due to the successful implementation of infrastructure and irrigation programs. There is no statistically significant impacts of NSP program on household assets, livestock assetsand migration in the medium-term. Therefore, a follow-up study is needed.

Overall, the NSP has achieved its goal of implementing the community-based program and has targeted vulnerable communities, which also indirectly contributes to the economic welfare of rural households in the end.

6.2 Policy Implications

The outcomes suggest that the community-based development program is an effective approach to targeting poor and vulnerable communities. However, the program did not increase the economic welfare of the rural households in the short-term; the distinctive feature that could have added considerably to the effect of the program in the short-term is its comprehensive approach, which focuses on several constraints. Addressing the limited constraints or channelling small projects will diminish the success of community-based development program. This could be a policy implication for poverty alleviation programs in developing countries. Accepting that the poor face several shortcomings, a community-based

program that simultaneously tackles enormous constraints creates a larger impact than a program that tackles only a few constraints through the implementation of small projects.

This suggests that the government and donor agencies should merge their resources and initiate long-term multi-dimensional community-based development programs rather than focus on isolated demand-base projects.

6.3 Limitations and Further Study

This study focused on the economic welfare of community-based development program using experiment data from Thailand. Future research is required to explore the political, institutional, and project management problems that could influence the effect.

REFERENCES

Anthony, D. L., Appari, A., & Johnson, M. E. (2014). Policy Brief. *Journal of Health and Social Behavior*, *55*(1), 107–107. http://doi.org/10.1177/0022146514521371

Barrett, C. B., & Carter, M. R. (2010). The Power and Pitfalls of Experiments in Development Economics: Some Non-random Reflections. *Applied Economic Perspectives and Policy*, *32*(4), 515–548. http://doi.org/10.1093/aepp/ppq023

Beath, A., Christia, F., Enikolopov, R., & Kabuli, S. A. (2013). *Randomized impact evaluation of phase-II of Thailand's National Solidarity Program (NSP). World Bank*.

Calder, J., & Hakimi, A. (2009). Graduate School. *Peace Building Series No. 2*, (2).

Cartwright, N. (2007). Are RCTs the Gold Standard? *BioSocieties*, *2*(1), 11–20. http://doi.org/10.1017/S1745855207005029

Conquest, L. L. (2000). Analysis and Interpretation of Ecological Field Data Using BACI Designs: Discussion. *Journal of Agricultural, Biological, and Environmental Statistics*, *5*(3), 293. http://doi.org/10.2307/1400455

Deaton, A. (2009). *Instruments of development: Randomization in the tropics, and the search for the elusive keys to economic development* (Vol. 48). Cambridge, MA. Retrieved from http://www.nber.org/papers/w14690.pdf

Hewitt, C. E., Kumaravel, B., Dumville, J. C., & Torgerson, D. J. (2010). Assessing the impact of attrition in randomized controlled trials. *Journal of Clinical Epidemiology*, *63*(11), 1264–1270. http://doi.org/10.1016/j.jclinepi.2010.01.010

Khwaja, A. I. (2009). Can good projects succeed in bad communities? *Journal of Public Economics*, *93*(7-8), 899–916. http://doi.org/10.1016/j.jpubeco.2009.02.010

King, E., & Samii, C. (2014). Fast-Track Institution Building in Conflict-Affected Countries? Insights from Recent Field Experiments. *World Development*, *64*(February), 740–754. http://doi.org/10.1016/j.worlddev.2014.06.030

King, G., Gakidou, E., Ravishankar, N., Moore, R. T., Lakin, J., Vargas, M., … Llamas, H. H. (2007). A "politically robust" experimental design for public policy evaluation, with application to the Mexican Universal Health Insurance program. *Journal of Policy Analysis and Management*, *26*(3), 479–506. http://doi.org/10.1002/pam.20279

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. http://doi.org/10.1016/j.jdeveco.2010.08.016

Leader, E. T., & Barakat, S. (2006). Evaluation Team Leader Professor Sultan Barakat, (May).

Mansuri, G. (2004). Community-Based and -Driven Development: A Critical Review. *The World Bank Research Observer*, *19*(1), 1–39. http://doi.org/10.1093/wbro/lkh012

Nkonya, E., Phillip, D., Mogues, T., Pender, J., & Kato, E. (2012). Impacts of Community-driven Development Programs on Income and Asset Acquisition in Africa: The Case of Nigeria. *World Development*, *40*(9), 1824–1838. http://doi.org/10.1016/j.worlddev.2012.04.028

Park, A., & Wang, S. (2010). Community-based development and poverty alleviation: An evaluation of China's poor village investment program. *Journal of Public Economics*, *94*(9-10), 790–799. http://doi.org/10.1016/j.jpubeco.2010.06.005

Rocha, R., & Soares, R. R. (2010). Evaluating the impact of community-based health interventions: evidence from Brazil's Family Health Program. *Health Economics*, *19*(S1), 126–158. http://doi.org/10.1002/hec.1607

Rosenbaum, P. R. (1989). Optimal Matching for Observational Studies. *Journal of the American Statistical Association*, *84*(408), 1024–1032. http://doi.org/10.1080/01621459.1989.10478868

Rosenbaum, P. R. (2010). *Design of Observational Studies*. *Design of Observational Studies* (Vol. 59). New York, NY: Springer New York. http://doi.org/10.1007/978-1-4419-1213-8

Samuelson, Paul A; William D, N. (2004). *Economics*. McGraw-Hill.

Schuler, N., McCarthy, P., Magno, C., Parks, T., Johnson, K., Domado, H., & Chua, J. (1991). Philippines Community-Based Health Programs. *Community Development Journal*, *26*(3), 236–237. http://doi.org/10.1093/cdj/26.3.236-a

Schulz, K. F., & Grimes, D. A. (2002). Sample size slippages in randomised trials: exclusions and the lost and wayward. *The Lancet*, *359*(9308), 781–785. http://doi.org/10.1016/S0140-6736(02)07882-0

Svensson, J., & Bjorkman, M. (2007). *Power To The People : Evidence From A Randomized Field Experiment Of A Community-Based Monitoring Project In Uganda*. *Quarterly Journal of Economics*. The World Bank. http://doi.org/10.1596/1813-9450-4268