Foreign Aid Allocation and Impact: A Sub-National Analysis of Malawi

Rajlakshmi De*
Professor Charles Becker, Faculty Advisor
Duke University

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Abstract

Understanding the role of foreign aid in poverty alleviation is one of the central inquiries for development economics. To augment past cross-country studies and randomized evaluations, this project estimates the first sub-national model of foreign aid allocation and impact. Newly geocoded aid project data from Malawi is used in combination with multiple rounds of living standards data to predict the allocation and impact of health aid, water aid, and education aid. Both instrumentation and propensity score matching methods are used in the impact models to adjust for aid being allocated non-randomly. Aid types are positively correlated, but other covariates of diarrhea incidence, geographic region, and rural setting, differed in their relationships with aid allocation. A significant, positive effect of health aid on decreasing disease severity and a significant, positive effect of water aid on decreasing diarrhea incidence were estimated through both instrumentation and propensity score matching. An appropriate instrument for education aid could not be determined, but propensity score matching methods estimated a positive effect of education aid on school enrollment. These results suggest that foreign aid plays a useful role in poverty alleviation in Malawi and that governments should use information about local disease severity, diarrhea incidence, and school enrollment to allocate different aid types more efficiently.

JEL classification: F35; O12; I15; I25; I32
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*Rajlakshmi De graduated from Duke University in May 2013 with High Distinction in Economics. She is currently a Research Fellow at Stanford Law School for the 2013-2014 academic year and can be reached at rajlakshmi.de@gmail.com. She is deeply grateful to Professor Charles Becker for his mentorship throughout the project.

1 Introduction

The first sub-national model of foreign aid allocation and impact is estimated in this paper to augment past cross-country studies and randomized evaluations. One of the main purposes of the sub-national approach stems from the need to assess aid on living standards variables that should be directly targeted by aid projects, such as disease reduction and increases in educational attainment. Employing sub-national variation should also reduce the vast unobservable differences that may be present in cross-country variation. Newly geocoded aid data for Malawi allows for both of these specifications. Aid projects are segmented by aid type and geographic administrative boundary and their allocations and impacts within Malawi are explored through living standards variables such as disease incidence and severity.

Past studies have explored the questions of aid allocation and impact using cross-country variation, but these studies lack agreement on whether aid policies are useful or destructive in developing economies. Furthermore, an important distinction is that those studies estimate the impact of aid on macroeconomic variables such as growth, whereas this paper's dependent variables are development outcomes surrounding health and education. There is also currently an expanding literature on the impacts of development programs using evidence from randomized trials. Those studies' dependent variables are usually living standards variables or other microeconomic outcomes, not economic growth rates, but an important distinction is that the randomized trials assess a particular experimental treatment, whereas this paper attempts to detect impacts from the roughly 5 billion dollars in existing Malawi aid projects in order to achieve greater external validity.

Malawi is the country of interest in this research for several reasons. Malawi is the first country to have comprehensive, geocoded data on aid projects. It received 5.3 billion dollars in foreign aid during the aid project datas time period of 2004 to 2011. Malawi's population and GDP in 2011 were 15.4 million and 5.8 billion dollars, respectively. These figures reflect a relatively small population for a developing nation and aid inflows over 8 years that are almost equivalent to current annual economic output. The combination of high aid and low population makes Malawi an appealing country in which to attempt to detect an effect of aid from sub-national variation across time. For this project, aid is investigated through three different sub-categories of aid: health aid, water and sanitation aid, which is referred to simply as water aid, and education aid. The geographic variation in aid allocations is based on the administrative boundaries of the 216 Traditional Authorities (TAs) monitored by the National Statistical Office of Malawi. The aid project data was captured in the Malawi Aid Management Platform (AMP) and geocoded by AidData and CCAPS. Living standards data was taken from the IHS2 and IHS3 rounds of the Malawi Living Standards Measurement Study (LSMS) from the National Statistical Office of Malawi and the World Bank.

By employing the sub-national model, this study contributes empirical results for the allocation and impact of health aid, water aid, and education aid. The allocation models are found to vary greatly in terms of the relationships with diarrhea incidence, regional dummies, and a rural dummy, whereas they all have positive relationships with other aid type allocations such that health aid, water aid, and education aid are positively correlated with one another. Impact regressions employ two complementary methods–instrumentation and propensity score matching–that account for the endogeneity of aid allocation but through two different mechanisms, serving as a robustness check of the impact estimates. Health aid is found to have a positive impact on decreased disease severity and water aid is found to have a positive effect on decreased diarrhea occurrence. Those results are supported by both the instrumentation and propensity score matching methods. Propensity score matching also provided evidence that education aid increases school enrollment, but the lack of an appropriate instrument for education aid prevented use of the instrumentation method for education aid. The overall importance of these empirical results is that not only are these aid types beneficial to poverty alleviation, but that the sub-national granularity in Malawi and using living standards data is an appropriate framework for modeling aid. The rest of the paper is organized as follows: In Sections II and III, the literature on aid allocation and impact is reviewed and a need for sub-national modeling using living standards variables is identified. Sections IV and V describe the data processing, empirical strategies employed and the findings obtained. Finally, concluding remarks will address the policy implications of this research.

2 Literature Review

As noted in the introduction, the current literature lacks a sub-national model that predicts aid allocation or detects impact. However, there is an expansive aid literature studying both allocation and impact, which is summarized below.

2.1 Allocation of Aid Projects

Allocation models have studied cross-country variation to determine the importance of economic needs, policy performance, political considerations, and strategic interests in explaining aid variation. Alesina and Dollar (2000) find that foreign aid is dictated as much by political considerations as by recipient economic needs and policy performance. They find that colonial past and political alliances are major determinants of foreign aid, and on the margin, countries that democratize receive more aid. Alesina and Dollar also find significant differences between donor countries in their aid allocation. The Nordic countries respond more to economic incentives, like income levels, good institutions and openness. France gives to former colonies tied by political alliances, without much regard to other factors, including poverty levels or choice of politico-economic regimes. The United States' pattern of aid giving is vastly influenced by interest in the Middle East (Alesina and Dollar 2000).

In contrast to Alesina and Dollar, Lumsdaine (1993) concludes that the donor country's "humanitarian concern" forms the basis of support for aid, not the donors political and economic interests. In his book *Moral Vision in International Politics: The Foreign Aid Regime, 1949-1989*, Lumsdaine uses theoretical and empirical representations of moral vision, the concept that donor nations view themselves as interdependent with recipient nations. Maizels and Nissanke (1984) focus on the variable of strategic foreign policy and use it to explain the pattern of bilateral foreign aid. They also find allocation models to be very different for bilateral and multilateral aid. Multilateral aid could be explained as compensating for shortfalls in domestic resources. Bilateral aid was generally explained as serving donor interests, such as political, security, investment and trade interests.

Kim and Oh (2012) focus their study on South Korea's aid allocation to 154 recipient countries, and find that South Korea provides more aid to higher-income developing countries with higher growth rates. They also find that the relationship between per capita incomes of the recipient country negatively correlated with aid allocation only for the middle-income or lower-middle-income group recipients and was correlated positively for the rest. No significant differences over decades or political regimes were found (Kim and Oh 2012).

There is a comprehensive literature that explains cross-country aid allocation. These studies are particularly useful in understanding political and strategic variables. This paper, however, aims to understand what sub-national factors are important in the question of aid allocation.

2.2 Impact of Aid Projects

Understanding aid's role in poverty alleviation is one of the most central inquiries for development economists. Despite the importance of the question, economists have not agreed on whether aid policies are useful or destructive in developing economies. Burnside and Dollar (2000) conduct a cross-country analysis of the role of good economic policies in aid effectiveness and found that aid has a positive impact on per capita growth in developing countries with good fiscal, monetary, and trade policies but has little effect in the presence of poor policies. They employ a modified neoclassical growth model that includes foreign aid receipts. Their policy variables are proxies constructed from the budget surplus, the inflation rate, and the openness dummy developed by Sachs and Warner (1995). Rajan and Subramanian (2005) also employ cross-country data and they use instrumentation to correct for the endogeneous allocation of aid to poorer countries, but unlike Burnside and Dollar (2000), they do not find evidence for an effect of aid inflows on national economic growth, even when economic policies are good.

These two important investigations highlight the large extent of disagreement with regards to aid impact when studied through cross-country comparisons, which may be because of the difficulty of detecting impacts on economic growth rates, which represent many more facets of the economy than the bottom of the pyramid targeted by most aid projects. Randomized control trials have been able to focus more on development outcomes and living standards rather than economic growth. In addition, their causal interpretation is more direct due to their inherent randomized design. This method has been employed to study various development question surrounding issues such as hunger, savings, consumption, and decisions surrounding health and employment. As a variation on randomized control trials, Miguel and Kremer (2004) evaluate a Kenyan project that treated intestinal helminthes, including hookworm, roundworm, whipworm, and schistosomiasis by using the fact that the program was randomly phased into schools. They estimate the overall programs effects to be that it reduced school absenteeism by one-quarter and was far cheaper than alternative ways of boosting school participation. Because they used the random phasing in, rather than a randomized control trial, they were able to find the effects of externalities as well, such as improved participation among neighboring schools.

A study by Baranov, Bennett, and Kohler (2012) investigated the "indirect impacts" of aid projects in Malawi. In particular, they investigate the impact of antiretroviral therapy (ART) on the indirect variables of the community's perceptions of mortality risk, mental health, and agricultural labor supply and output. Employing a difference-in-difference identification strategy, they find that the ART availability substantially reduced subjective mortality risk and improved mental health in rural Malawi. However, their study lacks a selection model, so makes the assumption that ART allocation is random or exogenous. Furthermore, because their study attempts to answer a question of indirect impact but only analyzes ART as the exogenous project, there may be a problem of omitted variable bias. Much of the impact they are finding could be attributed to other simultaneous aid projects, such as other health clinics or rural development programs that are influencing subjective mortality risk and labor force participation.

This paper attempts to address the void between cross-country studies and micro impact evaluations by employing the sub-national approach. The subnational approach should offer greater external and ecological validity than individual trials. In addition, the Theoretical Framework in Section 3 will explain the rationale of studying aid on a sub-national level compared to cross-country analyses and in particular why Malawi is well suited for these inquiries.

3 Theoretical Framework

There are three theoretical issues that motivate this paper's model. The first issue is concerned with measuring the impact of aid through dependent variables that are the most likely to be targeted by aid. The second and third issues are concerned with the importance of aid relative to other economic variations, which is a concept that motivates both the sub-national level of analysis and the study of Malawi in particular.

The most evident causal links between aid and economic development are going to be very targeted to the specific purposes of aid projects. In addition, the most detectable effects will be outcomes that can improve shortly after aid is disbursed. Therefore, to determine whether aid has a positive impact, and is not fully drained by corruption, the effect should be investigated on these direct, more immediate dependent variables of disease severity, diarrhea incidence and school enrollment. If aid is not fully absorbed by corruption, then its impact is likely to be found in these statistics because a project that purifies water has the purpose of reducing waterborne illness such as diarrhea. Similarly, health clinics should be reducing disease severity, which is measured by the number of days an individual is too ill to continue work. Education projects should be providing more schooling capacity such that school enrollment increases. The cross-country literature focuses its investigations on whether aid has implications for economic growth, balance of payments support, or other macroeconomic effects, which are very important questions, but in terms of detecting whether aid is helpful for development, it is more desirable to look at the variables where the impact should be expected, which is the methodology adopted by this paper.

In addition to more targeted variables, this paper notes that the importance of aid relative to other economic variations is an important consideration for evaluating aid impact. When measuring impact of aid, t-tests of significance are dividing coefficient estimates of impact by standard errors. The standard errors represent the variation in impact, so a greater variation across observations leads to significance being harder to detect. Given a constant impact estimate, a larger variation across individual impact measurements will lead to a decrease in the test statistic and increase overall insignificance. This motivates a sub-national, rather than cross-country, analysis. Within Malawi we expect less variation in how aid is affecting people than the variation that would exist in a diverse cross-country sample. If there is truly an impact of aid, the subnational model is an important level to investigate it.

This issue of relative importance also affects which countries are suited for an analysis of aid impact. Malawi received 5.3 billion dollars in foreign aid during the aid project data time period of 2004 to 2011. Malawi's population and GDP in 2011 were 15.4 million and 5.8 billion dollars, respectively. As mentioned in the Introduction, these figures reflect a relatively small population for a developing nation and aid inflows over 8 years that are almost equivalent to current annual economic output. The combination of high aid and low population suggests that the impact should not be completely diluted by the standard error term, which represents variations in outcomes. The relative size of aid in the economy and population is larger than in a highly populated and large economy like India, for example. This makes Malawi an appealing country in which to attempt to detect an effect of aid from sub-national variation across time.

4 Data

This project is possible because of recent advancements in data collection and geocoding. Two important sources of data are used: aid project data from aiddata.org and living standards data from the National Statistical Office of Malawi. Both sources have a high level of geographic specificity. The aid project dataset is based on information captured in the Malawi Aid Management Platform (AMP), hosted by the Malawi Ministry of Finance. In total, projects from 30 donor agencies were geocoded for 548 projects, representing 5.3 billion dollars in total commitments. This dataset represents the first effort to sub-nationally geocode all donors in a single partner country, making it essential for my analysis; however, the aid data are not free from limitations. The aid project data contains missing values for some geographic coordinates and some projects are geocoded but have locations in multiple TAs with only one value for cumulative disbursement of aid. My methodology has been to exclude the projects without any geographic information, because the empirical analysis is entirely geography-dependent. With regards to the cumulative disbursement figure for projects spanning multiple TAs, I have made an estimate of proportional project allocation by weighting aid project allocation by TA population size. The assumption inherent with this method is that if a project spans two TAs, with one having twice the population as the other, and the data does not give detail about how it is divided, my analysis treats the aid as allocated with two-thirds to the large TA and one-third to the smaller TA because it has one-third of the total project population. Though this assumption is required to continue the analysis, it should not pose any significant problems because there are many TAs that did not receive any aid. That means the analysis is very much driven by a binary presence or absence of aid, and exact allocations among the TAs that received aid are not going to dramatically alter findings.

The living standards data was provided by the National Statistical Office of Malawi and the World Bank. In particular, two rounds of the Living Standards Measurement Survey (LSMS) were used: the 2nd Integrated Household Survey (IHS2) from 2004-2005 and the 3rd Integrated Household Survey (IHS3) from

2010-2011. The living standards data was already coded by TA boundaries. The survey samples for IHS2 and IHS3 were drawn using a stratified sampling procedure and included 11,280 households and 51,127 individuals and 12,271 households and 59,251 individuals, respectively. The allocation and instrumentation methods are suited for analysis based either on a sample size of 216 TA units using means of the living standards data or using the full data using individuals. The first methodology weights each TA equally whereas the latter gives more empirical importance to TAs with greater living standards observations. Because neither is clearly correct, both representations are provided in the Empirical Specification. Propensity Score Matching methods, however, are only suited for the full data using individuals. Unfortunately, the living standards data does not currently have panel data; the IHS3 has households that will serve as panel data in the future, but presently the IHS series do not allow for direct comparison of individuals. In order to overcome the lack of panel data while still comparing outcomes of individuals from different TAs, a joinby merge of the data was used. The joinby specification merges individual observations within unique TAs in IHS2 with all other individual observations from the TA in IHS3. This maintains the uncertainty over which households in IHS2 and IHS3 should be merged with each other, while still allowing methods that are based on individual matching methods, such as propensity score matching.

Merging between living standards data and aid data was based on TAs. Aid was segmented by TA region and each household in a particular TA was merged with the aid per capita figures for that TA. Only aid projects implemented after 2004 were included in the merge such that the projects fall between IHS2 and IHS3 data collection. The living standards data was already coded by TA boundary. The aid data, however, had geocodes, so ArcGIS geospatial processing software was used to align aid projects into TA boundaries. In particular, the Spatial Join feature was employed, which uses a GIS map of Malawi to group geocoded aid projects into TA areas. Figure 2 is a visual representation of the Spatial Join between TA area and Health Aid projects. The Spatial Joins provided aid project data by TA, and total aid per TA was calculated and converted to aid per capita.

5 Empirical Specification

The empirical specification consists of three components. The first constructs allocation models to predict how health aid, water aid, and education aid are allocated between TAs and uses OLS regression techniques. The second category applies the allocation models as first stage regressions within an instrumentation approach to measure the impact of aid types. The third takes an alternative approach of propensity score matching (PSM) to determine aid impact by simulating treatment and control groups of individuals. These three methods and their results will be discussed in detail below. Using both instrumentation and PSM to measure impact serves as a robustness check, because instrumentation methods hinge on instruments that are exogenous to the dependent impact variables whereas PSM bias is actually reduced when the matching characteristics are related to the outcome (Chen, 2). For example, instrumenting Health Aid to find impact on disease severity cannot rely on an instrument like diarrhea incidence, because diarrhea incidence may affect disease severity independently of Health Aid. PSM methods, on the other hand, can successfully incorporate these confounding characteristics, but the limitation is that substantial overlap of the matching characteristics is required between "treatment" and "control" groups. These criteria will be explained in further detail in later sections, but an important note is the complementarity of the instrumentation and PSM methods.

5.1 Allocation Models

The allocation models employ standard OLS regression procedures to predict health aid, water aid, and education aid disbursement to different TAs. This allows sub-national estimations to the question of "Who gets aid and why?" and it also provides valuable information for both the instrumentation and PSM approaches to aid impact by delineating covariates that can be used as either instruments or PSM matching attributes. Two sets of allocation models are provided. Table 1 shows the three models using the full data of individual observations and Table 2 shows the same models with estimates based on the compressed data such that N=221 because each observation is a single TA. As stated in the Data section, there is not a clear answer to whether the models should favor TAs that have more living standards data available (Table 1) or whether the model should give equal importance to each TA (Table 2).

Table 1: Allocation Models Using Full Data (N=51,127)

	Health	Water	Education
Diarrhea Illness	-2.031***	0.823	1.466**
	(0.759)	(0.944)	(0.685)
Northern Region	-13.954***	-2.586***	7.901***
	(0.313)	(0.397)	(0.286)
Central Region	-15.170***	2.611***	10.631***
	(0.232)	(0.301)	(0.213)
Rural	-28.248***	3.881***	4.745***
	(0.339)	(0.449)	(0.325)
Health Aid		0.376***	0.588***
		(0.005)	(0.003)
Water Aid	0.243***		0.066***
	(0.003)		(0.003)
Education Aid	0.724***	0.126***	
	(0.004)	(0.006)	
Constant	39.301***	-0.377	-8.071***
	(0.352)	(0.488)	(0.352)
R-squared	0.6565	0.2699	0.5567

NOTE: ***indicates 1 percent significance; ** indicates 5 percent; * indicates 10 percent. Significance is based on a one-sided t-statistic.

To interpret Table 1, it is first interesting to compare across the three types of aid. The four non-aid covariates, Diarrhea Incidence, Northern Region, Central Region, and Rural, vary in their signs, magnitudes, and significance levels across the three types of aid. For example, reporting diarrhea illness during the past 2 weeks correlates to 2 fewer health aid dollars per capita, whereas it is associated with about 1.47 dollars more per capita in education aid. Most surprisingly, the estimate for water aid is the insignificant one. This seems problematic given that water aid should be targeting regions where diarrhea illness is frequent.

Regional dummy variables are significant for all aid types in Table 1, but their correlations with aid vary significantly. Southern Malawi is favored for Health Aid by about 14 dollars per capita compared to both other regions, whereas Central Malawi is favored for Water Aid and Education Aid, where the differences between the highest and lowest receiving regions (holding other covariates constant) is 4 dollars and 10 dollars, respectively. Being urban leads to 28 dollars more per capita health aid, whereas rural is favored for water and education, but only by 4 dollars and 5 dollars, respectively. Aid types are all positively, significantly correlated with one another, which will be discussed

Table 2: Allocation Models Using Compressed Data (N=221)

	Health	Water	Education
Diarrhea Illness	-178.088*** (89.393)	3.586 (114.409)	143.181** (78.322)
Northern Region	-17.961*** (5.049)	5.141 (6.580)	9.913** (4.496)
Central Region	-18.116*** (4.063)	13.331*** (5.309)	10.607** (3.645)
Rural	-27.939*** (4.787)	3.262 (6.535)	1.850 (4.510)
Health Aid		0.383*** (0.083)	0.558*** (0.046)
Water Aid	0.238*** (0.052)		0.101** (0.047)
Education Aid	0.729*** (0.060)	0.213*** (0.098)	
Constant	43.196*** (4.973)	-7.057 (7.326)	-7.790* (5.038)
R-squared	0.6990	0.3479	0.6024

NOTE: ***indicates 1 percent significance; ** indicates 5 percent; * indicates 10 percent. Significance is based on a one-sided t-statistic.

after Table 2. Health Aid is the most strongly predicted model overall, with the highest R-squared and most number of significant variables, and is followed by the model for Education Aid.

Table 2 shows that the compressed model does not alter any signs except for the Northern Region dummy for Water Aid. Health Aid maintains its high overall predictive power and significance on all covariates, whereas Water Aid is no longer significantly predicted by the Northern dummy or the Rural dummy. Education Aid also loses significance on the Rural dummy. The magnitudes on the diarrhea covariate are much larger, but this is because the diarrhea covariate now represents a mean incidence of diarrhea for each TA, so an increase in 1 now represents a much larger notion than in Table 1 where the diarrhea variable is a dummy for each individuals response about whether she has had diarrhea illness in the previous 2 weeks. Again, it is surprising that the diarrhea covariate is insignificant for water aid given that the water projects should be allocated in areas of high water borne illness.

Though the allocation of aid varies greatly depending on the type of aid, all three types of aid are positively predicted by one another. Their correlations are

Table 3: Aid Correlations

	Health	Water	Education
Health	1.0000		
Water	0.5080	1.0000	
Education	0.7267	0.4300	1.0000

also presented below in Table 3.The correlation between health aid and water aid of 0.5080 is particularly important in the analysis because health and water aid may affect similar living standards data, such as diarrhea illness or disease severity. It will therefore be important to control for health or water aid when the other is being tested causally. In the following section, these causal models will be explored further to investigate whether each aid types impact can be discerned.

5.2 Impact Models - Instrumentation Methods

Instrumentation is one method for overcoming the difficulties of endogeneity within the aid impact process. Instrumental variables (IV) techniques hinge on two assumptions: relevance and exclusion. Relevance was tested through standard first stage regressions and exclusion was based on some obvious theoretical knowledge–such as not using a diarrhea variable to measure the change in diarrhea incidence–and passing the overidentification test.

In these models, it is important to control for other types of aid because of the correlations discussed previously, but the causal estimation can only be applied to the variable that is being instrumented. For example, in Table 4, water and education are included in the regression because they may have a relationship with the dependent variable, but only health aid is instrumented, so only its coefficient is interpreted causally.

Table 4 shows a positive, significant impact of health aid on decreased disease severity (measured by the number of days spent incapable of working due to illness in the past 2 weeks) using the full data set of all individuals. For an extra per capita dollar of Health Aid, 0.019 fewer days are lost due to incapacity. At the average per capita Health Aid allocation of 9.67 dollars, this causes 0.18 fewer days to be lost every 2 weeks, and between the minimum of 0 dollars and the maximum of 285 dollars per capita, this causes 5.4 fewer days to be lost every 2 weeks, which may have important economic implications for people who

Table 4: Impact of Health Aid - Full Data

	Decreased Disease Severity
Health Aid (Instrumented)	0.019*** (0.0009)
Water Aid	-0.006*** (0.0003)
Education Aid	-0.002*** (0.0006)
Constant	1.367*** (0.0108)

NOTE:The rural dummy variable and the Central region dummy variable were instruments for Health Aid. ***indicates 1 percent significance; ** indicates 5 percent; * indicates 10 percent. Significance is based on a one-sided t-statistic.

Table 5: Impact of Health Aid - Compressed Data

	Decreased Disease Severity
Health Aid (Instrumented)	0.063* (0.041)
Water Aid	-0.022*** (0.009)
Education Aid	-0.025* (0.019)
Constant	1.431*** (0.241)

NOTE:The rural dummy variable and the Central region dummy variable were instruments for Health Aid. ***indicates 1 percent significance; ** indicates 5 percent; * indicates 10 percent. Significance is based on a one-sided t-statistic.

are unable to work due to severe illness. Health aid was instrumented using the rural dummy variable and the Central region dummy variable, which together passed both the first stage relevance test and the overidentification test for exogeneity. Table 5 presents the same regression with the compressed sample size weighting each TA equally. A higher effect of 0.063 was found, but it was less significant. Both regressions substantiate that health aid has a positive impact when investigated on variables that should be targeted by these health projects, such as reducing the number of days spent too ill to work.

Table 6 shows a positive, significant impact of water aid on decreased diarrhea illness (measured by a dummy variable for each individual of whether diarrhea illness was experienced in the past 2 weeks) using the full data set of

Table 6: Impact of Water Aid - Full Data

	Decreased Diarrhea Illness
Water Aid (Instrumented)	0.0002*** (0.00002)
Health Aid	-0.0001*** ($9.45e^{-06}$)
Southern	0.0055*** (0.00011)
Constant	0.0105*** (0.00009)

NOTE:The rural dummy variable and the Education Aid were instruments for Water Aid. ***indicates 1 percent significance; ** indicates 5 percent; * indicates 10 percent. Significance is based on a one-sided t-statistic.

Table 7: Impact of Water Aid - Compressed Data

	Decreased Diarrhea Illness
Water Aid (Instrumented)	0.00040 (0.00033)
Health Aid	-0.00023* (0.00017)
Southern	0.01153** (0.00554)
Constant	0.00588** (0.00354)

NOTE:The rural dummy variable and Education Aid were instruments for Water Aid. ***indicates 1 percent significance; ** indicates 5 percent; * indicates 10 percent. Significance is based on a one-sided t-statistic.

all individuals. An extra per capita dollar of Water Aid causes a 0.0002 drop in the dummy variable for diarrhea illness, which is a 3 percent decline in diarrhea compared to the mean level of 0.007. Water aid was instrumented using the rural dummy variable and the Education Aid per capita, which together passed both the first stage relevance test and the overidentification test for exogeneity. Table 7 presents the same regression with the compressed sample size weighting each TA equally. A higher effect of 0.0004 was found, but it was insignificant with a one sided p-value of 0.12. However, given the first regression and the near-significance of the second, the IV methods provide evidence that water aid has a positive impact when investigated on variables that should be targeted by these water projects, such as reducing the number of diarrhea incidents.

Unfortunately, despite high relevance, none of the covariates could pass the overidentification tests for Education Aid. This suggests that issues of geography and development are linked importantly to educational enrollment, so further research is required to find appropriate instruments for education. However, due to the differing assumptions of PSM methods, the impact of Education Aid will be explored in the next section.

5.3 Impact Models - Propensity Score Matching Methods

Propensity Score Matching is a separate method for assessing causality within observational data. Because its assumptions are modeled differently than those for IV, these PSM tests serve as robustness checks for the IV method. In Propensity Score Matching, confounding characteristics that both affect aid allocation and living outcomes are used as matching characteristics between individuals who receive aid and those who do not. These matching characteristics are converted to a Propensity Score for each individual and treated individuals are compared to untreated individuals with the nearest Propensity Score. Because PSM is a method for treatment and control groups, aid was converted to a dummy variable where Health Aid=1 if any health aid was received and Health Aid=0 if none was received. The same specification was used for Water Aid and Education Aid. Therefore these estimates will not be directly comparable to the IV estimates, but the signs of impact should be consistent.

An important requirement for PSM is that the treatment and control groups matching attributes need to contain significant overlap, yet these matching attributes still need to predict the treatment condition. The first step is therefore to find a specification of matching attributes that both predicts aid allocation

Table 8: Health Aid Probit Regression of Balancing Covariates

	Probit
Water Aid	0.0103*** (0.0004)
Education Aid	0.1003*** (0.0023)
Diarrhea	0.1791*** (0.0309)
Constant	1.3317*** (0.0055)

NOTE:To fulfill the balancing property and due to computing size, individuals who had both no health aid and no water aid were not included. ***indicates 1 percent significance; ** indicates 5 percent; * indicates 10 percent. Significance is based on a one-sided t-statistic.

and is somewhat balanced between individuals who have both received and not received aid. Table 8 shows the Probit regression for matching characteristics that fulfilled the balancing property. Water Aid, Education Aid, and Diarrhea Illness are all significant at $p<0.01$ in the Probit regression. It is especially important to include Education Aid because of the possibility that Water Aid may affect decreased disease severity, which is the dependent variable for health aid impact.

Once the balancing property is satisfied, each treated individual is matched to an untreated individual while minimizing the differences in Propensity Scores between matched individuals. This is referred to as Nearest Neighbor Matching, where Neighbor refers to individuals with very similar Propensity Scores. In the case of Health Aid, individuals with similar Water Aid, Education Aid, and Diarrhea Illness but different allocations of Health Aid are matched with each other to find the average treatment effect. Table 9 presents the results of the PSM for Health Aid treatment on decreased disease severity, the reduction in days in the past 2 weeks spent unable to work, due to disease. Whereas the IV estimates signified a marginal effect per dollar of per capita aid, the PSM estimates need to be interpreted as the average effect of aid for those who received it compared to those who did not. The Table 9 estimate therefore represents Health Aid, on average, causing 3.4 fewer days lost every 2 weeks due to illness. The distribution of health aid per capita is skewed right, so it is not useful to interpret this estimate at the mean of health aid. However, given that the average effect is being skewed by individuals who receive the maximum amount of

Table 9: Impact of Health Aid

	Decreased Disease Severity
Health Aid	3.363***
	(0.121)

NOTE:Health Aid was a dummy variable. ***indicates 1 percent significance; ** indicates 5 percent; * indicates 10 percent. Significance is based on a one-sided t-statistic.

health aid per capita (285 dollars), the PSM estimate seems consistent with the IV interpretation at the maximum health aid per capita, which was 5.4 days.

For the PSM on Water Aid, where Water Aid is a dummy variable representing whether someones TA received any Water Aid, the balancing property and relevance of covariates were achieved using Health Aid, Education Aid, and the Southern regional dummy. As before, it was imperative to include Health Aid because of its confounding effect on the dependent variable of reductions in Diarrhea Illness. Table 10 presents the Probit regression for the successful matching characteristics, which were all significant at $p<0.01$. After matching Propensity Scores between the treatment and control groups, the estimate for impact was obtained, shown in Table 11. Again, this represents the average treatment effect for receiving water aid, rather than the marginal effect per dollar as in the IV. The average effect of receiving water aid is a decrease of 0.046 in diarrhea occurrence over 2 weeks and is significant at $p<0.05$. Though this low estimate may raise concerns about economic significance, it is important to note that diarrhea illness in general was not highly reported. Of the 51,127 individuals interviewed in IHS2, only 352 reported diarrhea illness in the past 2 weeks, which corresponds with a mean value for the dummy variable of 0.007. Therefore, the improvement in water aid receiving TAs of 0.046 is economically very high. It either represents an overestimate or signifies that non-treated regions may have declined in their diarrhea incidences while treated regions concurrently improved. As with Health Aid, another reason for such a high PSM estimate is the right skewed distribution of Water Aid per capita allocations. At the maximum Water Aid of 322 dollars, the IV estimate for impact is 0.129, which contextualizes that the PSM estimate may actually be consistent with the IV and not be an overestimate.

Education Aids impact could not be estimated in the IV model due to no instruments passing the overidentification tests for exogeneity. However, PSM methods can be applied to endogenous matching characteristics. In fact PSM

Table 10: Water Aid Probit Regression of Balancing Covariates

	Probit
Health Aid	0.0454*** (0.0022)
Education Aid	0.0038*** (0.0012)
Southern	1.1217*** (0.0612)
Constant	-2.4956*** (0.0402)

NOTE:Based on a random sample of 10,000 observations due to software computing size. ***indicates 1 percent significance; ** indicates 5 percent; * indicates 10 percent. Significance is based on a one-sided t-statistic.

Table 11: Impact of Water Aid

	Decreased Diarrhea Illness
Water Aid	0.046** (0.023)

NOTE:Water Aid was a dummy variable. ***indicates 1 percent significance; ** indicates 5 percent; * indicates 10 percent. Significance is based on a one-sided t-statistic.

Table 12: Education Aid Probit Regression of Balancing Covariates

	Probit
Water Aid	0.0066***
	(0.0004)
Health Aid	0.0804***
	(0.0012)
Constant	-1.844***
	(0.0203)

NOTE:Based on a random sample of 20,000 observations due to software computing size. ***indicates 1 percent significance; ** indicates 5 percent; * indicates 10 percent. Significance is based on a one-sided t-statistic.

bias is actually reduced when the matching characteristics are related to the outcome (Chen, 2). Table 12 presents the Probit regression for Education Aid in which Water Aid and Health Aid were used as the endogenous matching attributes. They are both significant at $p<0.01$ and the balancing property was satisfied.

Finally, the impact of Education Aid was estimated on Increased School Attendance, where School Attendance was measured by a dummy variable of whether or not the individual had ever attended school. In that sense, School Attendance is a misleading variable name because it actually represents attending school at some point and does not necessarily measure current school attendance. It is however still a very useful measure because it measures differences in TAs that have had exposure to schooling environments and those that lack substantial facilities or where economic pressure prevents schooling. Table 13 presents the result of the Propensity Score Match and finds a positive impact of Education Aid on exposure to schooling and is significant at $p<0.10$. Though there is no IV estimate to check for the robustness of this estimate, the PSM results alone suggest that receiving Education Aid caused an average treatment effect of 6 extra people per 100 receiving exposure to school. If this is representative of the actual effect of education aid, it may suggest an important economic significance through more people gaining access to literacy and growth of human capital.

Overall there is no major discrepancy between the IV and PSM estimates. All three aid types are found to have positive effects on variables that should be targeted by aid projects, with Health Aid and Water Aid substantiated by both IV and PSM methods. These results suggest that aid plays a useful role

Table 13: Impact of Education Aid

	Increased School Attendance
Education Aid	0.061*
	(0.039)

NOTE:Education Aid was a dummy variable. ***indicates 1 percent significance; ** indicates 5 percent; * indicates 10 percent. Significance is based on a one-sided t-statistic.

in Malawi and that the effect is great enough to be detected despite the unknown variable of corruption and despite countrywide variation that may inflate standard errors. The policy implications of these results are described in the following Conclusion section.

6 Conclusion

Through a sub-national analysis of Malawi, we found that aid allocation models vary greatly across type of aid. Evidence of positive causal relationships between aid and living standards was found. In particular, Health Aid reduces disease severity, Water Aid reduces diarrhea illness, and Education Aid increases school exposure. These rather obvious seeming statements reveal one of the important aspects of the methodology used here: if the impact of aid is being investigated, the living standards variables most targeted by aid projects are the ones that should be modeled. Greater data availability can allow this shift from cross-country macroeconomic investigations to sub-national living standards inquiries.

One of the arguments against foreign aid is that the resources fund corruption and do not impact poverty variables such as health and education. These results cannot unfortunately reveal if all the money is being used for development, but they do suggest that resources are being funneled to poverty efforts because the overall impact can be detected across time when controlling for the endogeneity of aid allocation. Returning to the allocation results and given the positive impact of water aid on reducing diarrhea illness, it is disconcerting that diarrhea illness was not a significant predictor of water aid allocation. This suggests that aid is being inefficiently allocated. Policymakers should attempt to design aid policies that are dependent on living standards data for all three of these aid categories: health aid should be concentrated where diseases are burdening people beyond the capacity to attend to employment, water aid should be reallocated towards high diarrhea regions, and education aid should be funneled to the areas with the least exposure to schools.

Goal 1 of the Millennium Development Goals is to reduce extreme poverty, and projections used by the United Nations indicate that almost one billion people will still be living on less than 1.25 dollars per day in 2015 (United Nations). Overcoming poverty is also one of the major goals for many different disciplines that are concerned with the economic, ethical and humanitarian implications of global suffering. However, this is an exciting time for development economists in particular to overcome past challenges in poverty reduction. Sub-national modeling should be further explored as a means for understanding the intricacies of development while maintaining external validity for an entire nation. Malawi's next round of living standards data will contain panel observations linked to IHS3 and provide an even stronger basis for assessing the impacts of various aid types, and as data becomes available for other nations' aid projects, sub-national analyses should be employed to assess foreign aid around the world.

References

[1] Alesina, Alberto, and David Dollar, *Who Gives Foreign Aid to Whom and Why?*, Journal of Economic Growth. **5** (2000), 33–63.

[2] Baranov, Victoria, Daniel Bennett, and Hans-Peter Kohler, *The Indirect Impact of Antiretroviral Therapy*, PSC Working Paper Series, PSC 12-08 (2012).

[3] Boserup, Ester *The Conditions of Agricultural Growth: The Economics of Agrarian Change under Population Pressure* (1965), London, United Kingdom: G. Allen and Unwin.

[4] Burnside, Craig, and David Dollar, *Aid, Policies, and Growth*, American Economic Review. **90** (2000), 847–868.

[5] Chen, Xi, *Propensity Score Matching*, Self-published, <http://web.cenet.org.cn/upfile/110244.pdf>.

[6] Galiani, Sebastian, Paul Gertler, and Ernesto Schargrodsky, *Water for Life: The Impact of the Privatization of Water Services on Child Mortality*, Journal of Political Economy. **113** (2005), 83–120.

[7] Kim, Eun Mee, and Jinhwan Oh, *Determinants of Foreign Aid: The Case of South Korea*, Journal of East Asian Studies. **12** (2012), 251–273.

[8] Lumsdaine, David Halloran *Moral Vision in International Politics: The Foreign Aid Regime, 1949–1989* (1993), Princeton, NJ: Princeton University Press.

[9] Maizels, Alred, and Machiko Nissanke, *Motivations for Aid to Developing Countries*, World Development. **12** (2012), 251–273.

[10] Miguel, Edward, and Michael Kremer, *Worms: Identifying Impacts on Education and Health in the Presence of Treatment Externalities*, Econometrica. **72** (2004), 159–217.

[11] Rajan, Raghuram, and Arvind Subramanian, *Aid and Growth: What Does the Cross-Country Evidence Really Show?*, IMF Working Paper 05/127. **12** (2005), International Monetary Fund, Washington, D.C.

[12] United Nations *Millennium Development Goals. Goal 1: Eradicate Extreme Poverty and Hunger*, <http://www.un.org/millenniumgoals/poverty.shtml>.