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EMPIRICAL ESSAYS ON THE IMPACT OF HEALTH-AID ON HEALTH OUTCOMES

by

Elsy Thomas Kizhakethalackal

A Dissertation
Submitted to the
Faculty of The Graduate College
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Advisor: Debasri Mukherjee, Ph.D.

Western Michigan University
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EMPIRICAL ESSAYS ON THE IMPACT OF HEALTH-AID ON HEALTH OUTCOMES

Elsy Thomas Kizhakethalackal, Ph.D.

Western Michigan University, 2009

This dissertation consists of three essays that empirically explore the impact of multilateral health-aid on health outcomes like infant mortality rate (IMR) and incidences of an infectious disease, Tuberculosis, in developing economies. The first essay uses parametric and semiparametric mean regressions (additive and non-additive specifications) to capture the impact of education and health-aid on the IMR, after controlling for other covariates. Both specifications confirm education as an important factor in reducing IMR. However, the effect of health-aid on IMR is not significant. In our additive model, we do see a threshold level of health-aid after which the impacts of health-aid are always negative, as expected, from positive.

In the second essay, the study continues to focus on the same relationship. However, we use parametric and semiparametric quantile regression approach. This approach helps capture the effect of health-aid on various groupings/quantiles of infant mortality rates. Our estimation procedures confirm that education and gross domestic product play significant roles in improving health standards across all quantiles of IMR. We do not find any robust evidence of health-aid significantly lowering IMR in any quantile of IMR.

The third essay uses annual level data to explore the dynamic nature of the impact of health-aid on Tuberculosis. The findings from both our dynamic panel specifications—differenced generalized method of moments (GMM) and systems GMM—confirm that, among the covariates considered, education does play a significant role in lowering the incidences of Tuberculosis. Unfortunately, the dynamic panel estimations reveal that health-aid not only has the wrong sign in some cases but is always ineffective in lowering the incidence of Tuberculosis.

Thus, the policy implications of our analyses are that health-aid does not work and, therefore, better monitoring of the aid disbursement and usage is required. Donors should also focus on improving basic education level which by itself can help health outcomes through increased awareness of nutrition, prevention of diseases, and treatment.

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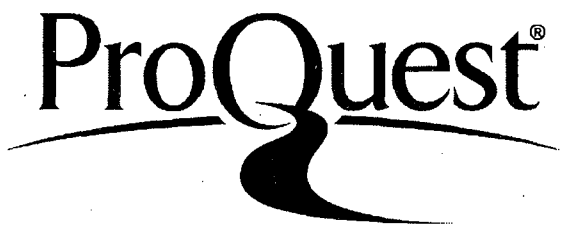

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Elsy Thomas Kizhakethalackal

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CHAPTER I

INTRODUCTION

Foreign aid is disbursed to developing countries to meet the existing resource crunch and help achieve growth targets. With the recent emphasis being placed on improving human infrastructure, a large portion of the aggregate aid is diverted toward specific sectors and purposes (see Millennium Development Goals). Though a lot of empirical evidences that test for the effectiveness of aggregate aid on growth outcomes are available, not much research is done in exploring the impact of disaggregated aid: health-aid on health outcomes. Using newly available disaggregate data on health-aid from the Organization for Economic Co-operation and Development (OECD), our dissertation explores the impact of health-aid on health outcomes like infant mortality rate and incidences of an infectious disease (tuberculosis) in developing economies.

The first essay analyzes the impact of foreign aid given for health purposes on the infant mortality rate (IMR), which is a key health standard indicator. The work also assesses the importance of primary completion rate (used as a proxy for education and as a quality measure of existing human infrastructure in the recipient country) and health-aid in reducing IMR (after controlling for other variables such as GDP per capita, physician stock [used as a proxy for health infrastructure], population, and regional dummies) in a semiparametric setting. The semiparametric regression method does not specify any a-priori functional form for the relationship of interest and allows the data to reveal the underlying functional relation. Statistical tests help validate the nonlinearity among the

combined effects of health-aid and education on IMR. Such a specification also allows us to examine the varying effects of health-aid on IMR in various ranges of the sample (i.e., for various levels of health-aid and education). We use two semiparametric specifications: an additive specification, which allows us to analyze the individual effect of health-aid on IMR and education on IMR; and a non-additive specification, which analyzes the joint effects between health aid-education on IMR. Both our specifications confirm education as an important factor in reducing IMR. However, the effect of health-aid on IMR is not robust across the two specifications. In our non-additive specification we find a large percent of the partial effects corresponding to health-aid are insignificant (around 68%), implying that aid does not work in general. We find very few of the partial effects of health-aid to be positive and significant and some of them to be negative and significant. Our additive model specification does not show any such pattern or significance. However, we do see a threshold level of health-aid (i.e., when health-aid reaches a value of 6 [in log terms] i.e., about $403), after which the point-wise estimates corresponding to health-aid are always negative, as expected from positive. Hence, combining the results of the two models we conclude that developing countries need not only a high amount of health-aid but also better monitoring of the purpose for which health-aid is actually being used.

In our second essay we continue to focus on the same relationship; however, we use a different modeling technique. Developing countries can be categorized into various "clubs/groups" based on the extent of poverty, human infrastructure, and health standards they face. An interesting question that emerges is to what extent health-aid can be useful to country groups with very high levels of poverty (or very poor quality of human

infrastructure or health standards) versus countries with not so severe levels of poverty or poor human infrastructure or health standards, i.e., the work explores how health-aid affects IMR at different levels (quantiles) of IMR. Thus, using quantile regression, we can explicitly capture the effect of health-aid on various groups of developing countries (very poor vs. not so poor), in particular. This new regression technique, though recently used in aid-growth context, has never been applied in the health aid-health outcome context. This regression technique is also robust to the presence of outliers, which is common in the data of developing countries. Another advantage of quantile regression is the fact that any quantile can be estimated; thus, one can examine the issue for various different country groups based on poverty levels.

This chapter applies two different instrumental quantile regression estimation techniques that take care of the endogeneity issue: parametric quantile regressions and semiparametric quantile regressions, and we also compare our results to the analogous parametric and semiparametric mean regressions. Both our estimation procedures confirm that primary levels of education and GDP play a significant role in improving health standards across all quantiles of IMR. We find countries belonging to Sub-Saharan African regions are associated with high IMR, in all quantiles of IMR. In our semiparametric quantile regression estimation we also find physician stock plays a crucial role in lowering infant deaths especially from the 75^{th} percentile onwards, i.e., health infrastructure helps lower infant deaths especially in countries with high IMR. Surprisingly, in our parametric quantile specification we do find health-aid to be effective only at the lower quantiles of IMR (i.e., in the countries with lower infant deaths). Thus countries at the lower end of the distribution, i.e., with already low IMR, seem to have a

further gain from health-aid, while countries at the higher end of the distribution do not stand to benefit from the health-aid. In our semiparametric specification, however, health-aid is ineffective across all quantiles of IMR. Since our semiparametric quantile specification is a more superior technique and provides a better goodness-of-fit (which is reflected in the R square values) than the parametric counterpart, we can conclude that there is no robust evidence that health-aid significantly lowers IMR in any quantile of IMR. The corresponding two stage estimations under both the parametric and semiparametric mean regression specifications confirm to these findings.

From the different estimation techniques applied in our first and second essays, we conclusively observe the ineffectiveness or failure of health-aid on IMR. The third essay focuses on impact of health-aid on tuberculosis. Tuberculosis is one of the most widespread infectious diseases that largely affect the economically productive age group of 15-59 years in developing countries. In this essay we apply standard linear mean regression specifications to annual level data and explore the dynamic nature of the relationship to check for any significant impact of health-aid on this specific infectious disease. The findings from both dynamic panel specifications—differenced GMM and systems GMM—confirms that among the covariates considered education does play a significant role in lowering the incidences of tuberculosis. Unfortunately the dynamic panel estimations reveal that health-aid not only has the wrong sign in some case but is always ineffective in lowering the incidence of tuberculosis. In the systems GMM specification we find government efforts may help in improving health outcomes along with health-aid but not by itself. We also find support for the contagious nature of the disease in our systems GMM specification.

Thus, to conclude from our three empirical estimations, we always find the impact of health-aid on health outcomes to be insignificant. We also find primary education levels to play a key role in lowering health outcomes. The main policy implication would be to channelize a part of the health-aid toward improving the stock of human infrastructure (education) and health infrastructure (health personnel). Aid could be diverted toward meeting basic educational standards, generating more public awareness on health care and nutrition and child care issues, which would help improve health knowledge and practices.

CHAPTER II

THE EMPIRICS OF HEALTH-AID AND INFANT MORTALITY: A SEMIPARAMETRIC STUDY

Introduction

One of the major indicators that helps capture long-term improvements in health and welfare in developing countries is the infant mortality rate (IMR). Developing countries have received considerable foreign aid over the last five decades or so. Surprisingly, however, relatively higher aid receiving regions (Sub-Saharan Africa, for example) have experienced much lower growth, lower poverty reduction, and lower health standards than relatively low aid receiving regions (like East Asia). This has led to much skepticism and scrutiny into the effectiveness of foreign aid. Despite the vast literature considering the effects of foreign aid on economic growth and poverty, there is little systematic empirical evidence on how overall aid affects health, and even less on how health-aid affects health outcomes. This chapter aims at assessing the impacts of health-aid and completion of basic levels of education (i.e., primary completion rate) on infant mortality rates.

This chapter contributes to the literature in two ways. First, we add to the literature by focusing on the disaggregated component of aid that is specifically directed to health outcomes (referred to as health-aid) as opposed to aggregate aid, and assess its impact on infant mortality, which is a key indicator of health as well as welfare in aid receiving countries. We also examine the role of education as measured by the primary

completion rate in this context. Using a newly available data set from OECD that provides detailed information on health-aid disbursed to developing countries, we examine the impact of health-aid on the IMR and the role of education in this regard—issues that have not received much attention yet. Second, to the best of our knowledge, this is the first study that attempts to explore the relationship between health-aid and IMR (health-aid and education) in a data-driven (nonparametric) way. We use nonparametric estimation to understand the effect of health-aid on IMR. This estimation framework does not assume any a-priori functional form for the main relationships under scrutiny. Instead the data are allowed to reveal the underlying shape of the relationship of interest (IMR-health aid) by avoiding any functional form misspecification bias in the relationship of interest. The other covariates like physician stock, population, GDP and the regional dummies enter the model parametrically. Since some of our variables are treated parametrically and some are treated in a nonparametric fashion (the key variables of interest), our overall estimation strategy is partially linear, i.e., semiparametric. The semi/nonparametric modeling also allow us to examine the varying effects of health-aid on the IMR in various ranges of the sample (i.e., for various levels of health-aid). This is a major advantage of the semiparametric estimation that we are using. We use both additive and non-additive model specifications (details to follow) to test this relationship.

Using an unbalanced panel consisting of 110 developing countries spanning the time period from 1974 to 2005, we find that the partial effects of health-aid does not always seem to affect the IMR significantly in either of our semiparametric model specifications—additive or non-additive. In our non-additive semiparametric model specification we find that around 68% of the coefficients (partial effects corresponding to

health-aid) are insignificant, implying that aid does not work in general. We find very few of the partial effects of health-aid to be positive and significant and some to be negative and significant. In our additive semiparametric model specification we do not find health-aid to have any significant impact on health outcomes in any range of the sample. However, we do see that after a threshold level of health-aid is reached the point-wise estimates become negative, as expected, from positive. Our results have important policy implications. Combining the results from the two models we may conjecture that developing countries may need a high amount of health-aid and, more importantly, much better scrutiny is required to explore the reasons behind such ineffectiveness of aid. We also find that factors like education and per-capital levels of income always play a crucial role in improving health outcomes.

Literature Review

This section reviews studies that contribute to our knowledge of the effectiveness of aid on health outcomes. The literature focusing on the aggregate aid-IMR relation is surprisingly limited, and to our knowledge there is only one paper looking into health aid-IMR relation. Most cross-country econometric studies of aid concentrate on the effectiveness of aggregate aid in increasing economic growth. See, for example, Burnside and Dollar (2000), Collier and Dollar (2002), Easterly, Levin, and Roodman (2004), Burnside and Dollar (2004), and Dalgaard, Hansen, and Tarp (2004), to name a few. Burnside and Dollar (2000) argue that foreign aid can increase economic growth only if the aid recipient countries have "good macroeconomic policy." They measure "policy" by taking a linear combination of the budget deficit, inflation, and openness. This policy

variable serves as a proxy for existing macroeconomic conditions needed to foster economic growth. Although some empirical papers support this argument, several other papers dispute this view. Easterly et al. (2004) and Dalgaard et al. (2004), for example, show that the above policy view is not robust to the choice of sample. Several papers also argue that aid works by itself but with diminishing returns (see, for example, Hansen and Tarp, 2001). Thus, some papers introduce a square term for aid (assessing diminishing returns), while others use an aid-policy interaction term (examining if aid is more growth enhancing in a better policy environment) or aid^2-policy interaction term (trying to review both).

There is no clear consensus on the effectiveness of aid or the functional form through which aid (or aid and policy jointly) affects growth. A recent paper by Alvi, Mukherjee, and Shukralla (2008) uses a similar semiparametric data-driven estimation framework (which we are also using in this chapter) and reconciles some of the aforementioned controversies. Analogous arguments and skepticisms also carry over regarding the effectiveness of health-aid in reducing the IMR or the role of education in that context. Note that while the "policy" variable proxies for the existing macroeconomic pre-requisites/conditions in the aggregate aid-growth context, in the health aid-IMR context we use primary schooling completion rate as a proxy for education, which captures the existing quality of human infrastructure in a given population. Physician stock is used as a proxy for existing health infrastructure. Both these covariates can be considered as important pre-requisites in lowering IMR among developing countries. In this chapter our emphasis is on primary completion rate, an important pre-requisite variable to help improve health outcomes.

As mentioned before, the literature assessing the impacts of aid (aggregate) on the IMR is somewhat limited. Boone (1996) examines the impact of overall foreign aid on infant mortality, and considers an interaction term between aid and the political regime. He concludes that under certain political regimes aid does lower infant mortality. Masud and Yontcheva (2005) empirically study the effect of foreign aid (bilateral aid and aid given by Non Governmental Organization [NGO]) on infant mortality in developing countries. They suggest that NGO aid significantly reduces infant mortality. However, bilateral aid does not have any significant impact on infant mortality. Gomanee, Morrissey, Mosley, and Verschoor (2005) use cross-country data on low and middle-income countries to assess the impact of total aid on aggregate welfare measures like infant mortality and the Human Development Index (HDI) in recipient countries. They find that aggregate aid affects HDI, but does not have a significant impact on infant mortality.[1]

The empirical literature is surprisingly silent about the impact of health-aid on infant mortality. This could be attributed to lack of available data in the past. Recently, however, the OECD database (to be discussed below) has included data on health-aid given to developing countries. To our knowledge, the only other paper that discusses the impact of health-aid on the IMR is by Mishra and Newhouse (2007). Using a linear parametric framework, they find that increased health-aid is associated with a reduction

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[1] HDI is an index that measures different dimensions of quality of life, namely longevity, education, and access to resources.

in infant mortality, although their conclusions are not robust to the use of different variables and samples.

Data and Some Descriptive Statistics

Data

Our sample covers 110 developing countries spanning from 1974 to 2005. Following the conventional aid-growth literature, we use four-year averages. The periods are 1974-1977, 1978-1981, 1982-1985, 1986-1989, 1990-1993, 1994-1997, 1998-2001 and 2002-2005; thus we have a total of 8 time periods. However, this is a highly unbalanced panel often leaving only two or even one observation (time period) for many countries. Such limitations are mainly due to the health-aid variable. Our pooled sample has a total of 327 observations.[2] The dependent variable is infant mortality per 1000 live births. The independent variables are GDP per 1000 of the population measured in constant 2005 U.S. dollars; the primary schooling completion rate, which is used as a proxy for education; total population; health-aid per 1000 of the population measured in constant 2005 U.S. dollars; and the number of physicians per 1000 people. Physician stock is used as a proxy measure for the existing health infrastructure. The primary completion rate is used as a proxy for education captures the existing quality of human

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[2] We delete some outliers from our data. We detect outliers based on the *leverage value, RSTUDENT, COVRATIO* and *DEFIT* criteria. See SAS version 6 (4th edition) for the details. Afghanistan (1986-1989), Central African Republic (1978-1981), Equatorial (2002-2005), Korea Republic (2002-2005), and Marshall Island (2002-2005) were detected as outliers. Hadi (1992) method also detects the same outliers. The list of countries used in the sample is given in Appendix A.

infrastructure. Following the aid literature, we also include dummies for Sub-Saharan Africa and East Asia Pacific regions to control for some regional specific effects.

Our most important variable of interest is health-aid—aid that is specifically oriented toward promoting better health standards. The OECD database provides data on Official Development Assistance (ODA) commitments by purpose, taken from the Credit Reporting System (CRS). We use a specific set of health codes as defined by the CRS for compiling data on health-aid. Aid is defined as the sum of grants and concessional loans. Health-aid includes aid disbursed for the purpose of health policy and administrative management, medical training/education, medical research, medical services, basic health care, basic health infrastructure, basic nutrition, infectious disease control, health education, malaria control, tuberculosis control, and health personnel development. A detailed explanation on these health codes is given in Appendix A. We use Net ODA disbursement figures. Health-aid per 1000 of the population is in constant 2005 U.S. dollars. The variables and data sources are described in detail in Appendix A.

Some Descriptive Statistics

Table 2.1 gives us the summary statistics. The average IMR across the sample is around 74 infant deaths per 1000 live births. IMR range from as low as 6 per 1000 to as high as 191 infant deaths in some developing countries. For the sample as a whole the primary completion rate is about 63%. There is a vast disparity among the physician stock across countries. We find that the availability of physician per 1000 of the population is very low in some countries and as high as only 5 physicians per 1000 people, which reflects the poor health infrastructure among countries. The population

level also varies across the sample. On an average the amount of health aid disbursed per 1000 people is about 7.66 (in log terms), which amounts to $2124 (in constant 2005 U.S. dollars).

Table 2.1: Sample Summary Statistics

Variable	Mean	Std. Dev.	Min	Max
IMR	73.47	41.05	5.64	191
Health-aid	7.66	1.46	1.05	11.47
GDP	17.71	1.09	15.65	20.64
Education	63.43	28.95	10.30	128.69
Physician	0.52	0.79	0.001	5.19
Population	15.87	1.80	10.78	20.99

Note: GDP and Health-aid are per 1000 of the population and in constant 2005 U.S. dollars. Population, GDP, and Health-aid are in log terms.

Table 2.2 gives us an idea about the regional distributions of infant mortality rates around the world in 2005. From the table it is clear that the largest percent of IMR occur among Asian economies, i.e., about 54% followed by Africa, which accounts for about 40% of the infant deaths. This could be attributed to factors like low levels of education, lack of health infrastructure, low per capita incomes, etc., which are more prominent than other factors.

Table 2.2: Infant Mortality Rates Across the Main Regions of the World in 2005

Region	IMR	
	Number (millions)	Distribution (%)
Asia	4.08	54
Africa	3.06	40
Europe	0.05	1
Latin America	0.34	4
North America	0.03	0.40
Oceania	0.02	0.26
World	7.57	100

Source: United Nations, World Population Prospects, the 2006 Revision, 2007, www.inedd.fr

Estimation Method and Statistical Tests

The novelty in our estimation lies in using a semiparametric approach to explain the effects of our main variables of interest on the infant mortality rate (IMR). There would be a misspecification bias if one imposes a functional form (i.e., a parametric linear or nonlinear model) that is not consistent with the true functional relationship.

Since education is an important pre-requisite that affects health outcomes, we examine the role of education, health-aid on IMR. There is no consensus in the literature regarding the functional form of the health aid-education-IMR relationship. Thus we explore the relationship in a data-driven way. We explore the relationship between health aid-education-IMR in a semi/nonparametric fashion. The other covariates are treated linearly.

We first consider a non-additive semiparametric specification. The partially linear model that we use is as follows:

$$Y = X\beta + f(Z) + U$$

or
$$Y = X\beta + f(\textit{health-aid, education}) + U \quad (1)$$

The choice of the modeling strategy is backed up by several statistical tests to be discussed below. Here Y is the dependent variable (IMR), X is the set of relevant macroeconomic control covariates modeled linearly (such as physician stock, gross domestic product per 1000 of the population, population, population square, and the regional dummies), β is the associated parameter vector, Z is the set of variables treated nonparametrically (i.e., health-aid and education variable), $f(.)$ is the unspecified (nonparametric) functional form capturing the joint effects of our variables of interest (health-aid and education) on infant mortality and U captures i.i.d. and homoscedastic errors. Note that $f(.)$ symbolizes a general function, which does not superimpose any particular functional form specification (linear or quadratic or exponential or so), and therefore the effects of health-aid and education on the IMR are determined in a nonparametric or data-driven way. Thus we allow the data to estimate the functional relation rather than superimposing any functional form which we do not know for certain. Thus the regression model above is a partially linear or semiparametric model that combines parametric and nonparametric modeling. Note that the control covariates denoted by X are modeled linearly and parametrically. Our estimation strategy is also statistically validated by several important tests. We perform a new nonlinearity test as in Hsiao, Li, and Racine (2007). The test considers a null of a fully linear model against an

alternative of a fully nonparametric model.[3] The *p*-value of this test is 0.000, suggesting that the null of linearity is strongly rejected.

A pure nonparametric approach has several costs associated with it. The dimensionality problem is a major concern. One requires a large sample where the size of the sample required increases rapidly with the number of regressors that are treated nonparametrically.[4] Given our sample size, which is a potential limitation, this is overcome by using a partially linear/semiparametric model as in (1). However, the abovementioned Hsiao et al. (2007) test does not tell us which of the variable(s) drive the underlying nonlinearity. So we perform the Li, Huang, Li, and Fu (2002) test, which shows that the combined effects of health-aid and education on the IMR are particularly nonlinear. This tests for functional form misspecification, where the null is a linear parametric model (linear in all variables) and the alternative is a partially linear model as in (1). This test allows us to detect nonlinearity in a particular variable (or in a set of variables). Bandwidth choice is always an issue in nonparametric regressions under kernel smoothing and there are several competing options available for that. We performed these tests using different bandwidths including optimal bandwidth (minimizing integrated mean square error), and least square cross validated bandwidth (minimizing integrated squared error) to check for the robustness of our test results.[5] While testing for nonlinearities in the health-aid and education variables, we obtain *p*-

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[3] A fully nonparametric model does not assume any functional form for any covariate. That is, the model will be $Y = m(X, Z) + U$, instead of the partially linear model as in (1).

[4] See Robinson (1998), Li and Stengos (1996), Pagan and Ullah (1999), and Li and Racine (2007) for the details.

[5] See Li and Racine (2007) for details.

values to be consistently low, ranging from 0.001 to 0.010 (depending on the bandwidths used). Thus the tests reject the null hypothesis of health-aid and education being linear. For the other variables, *p*-values of the test statistics range from 0.114 to 0.566, supporting linearity in those variables with the exception of the population variable. The nonlinearity in the population variable is taken care of by introducing a quadratic term.[6]

We are primarily interested in *f(.)* i.e., the fitted health aid-education-IMR relation after controlling for the other covariates *(X)*, the partial effects of health-aid (haid) on the IMR, i.e., $\frac{\partial IMR}{\partial haid}$ and the partial effects of education (edu) on the IMR, i.e., $\frac{\partial IMR}{\partial edu}$, both of which are expected to be negative. We are also interested in the second cross partial $\frac{\partial^2 IMR}{\partial haid \partial edu}$ to check if higher levels of education (i.e. primary completion rate) can increase health-aid effectiveness on the IMR, to be discussed later.

One may be concerned with the effects of time invariant country specific heterogeneities in the regression. To our knowledge, fixed effect unbalanced panel regression results are not yet developed for the nonparametric/semiparametric framework under kernel smoothing. As mentioned earlier, our objective is to use as much data information as possible. Hence we consider an unbalanced panel; otherwise, the loss of observations would be quite substantial. Also note that for many countries we have very few time periods, one or two only. About 9% of the countries in our sample have only one time period and therefore any first difference or within estimator in a fixed effect

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[6] Note that population is not our primary variable of interest.

setting would simply drop those countries.[7] Therefore, following the aid literature we use two regional dummies (Sub-Saharan Africa and East Asia) to capture some regional specific effects. One may also be concerned with the strict exogeneity of the covariates. Because the aid-growth-poverty literature does not consider aid as a strictly exogenous variable, we use a one period lag of health-aid instead of current period health-aid to subdue any possible endogeneity effect. This is consistent with the usual practice in the aid literature. Note that Dalgaard et al. (2004) have shown that one period lag of aid serves as the best instrument for aid. We ran Wu-Hausman (1978) test for endogeneity and failed to reject the null of strict exogeneity for the other continuous variables at the 5% level. See Davidson and MacKinnon (2004) for details on this test.

Thus we use pooled data for all countries and years together and use local kernel based semiparametric regression. Li and Stengos' (1996) approach incorporates both predetermined and strictly exogenous regressors as it is compatible with our set of covariates.[8] Our partially linear model not only takes care of any possible functional-form misspecification in our main variables of interest (health-aid and education), it also sheds light on how these variables affect the IMR in various regions of the sample. We are able to capture the varying effects on infant mortality at different levels of health-aid and education. This is a major advantage of semiparametric estimation (local kernel weighted estimation as in Li and Stengos, 1996) that we are using.

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[7] A dynamic panel specification cannot be considered. This is mainly because about 58 countries out of 110 countries in our sample have less than 3 time periods.

[8] See Robinson (1988), Pagan and Ullah (1999), and Li and Racine (2007) for more details on semiparametric and nonparametric regressions, their asymptotic properties, as well as some applications.

As a robustness check we also consider an additive semiparametric specification. Rather than looking at the joint effects of health aid-education-IMR relation, we check out the effects of health-aid and education independently. Health-aid and education variables enter the semiparametric estimation additively.[9] We do not assume any a-priori functional form specification for our variables of interest namely health-aid and education, all the other covariates enter linearly. The partially linear model that we use under the additive specification is as follows:

$$Y = X\beta + f(Z_1) + g(Z_2) + U$$

or
$$Y = X\beta + f(\textit{health-aid}) + g(\textit{education}) + U \qquad (2)$$

where Z_1 and Z_2 correspond to the semiparametric variables, i.e., health-aid and education which enter additively, *f(.)* and *g(.)* is the unspecified (nonparametric) functional form capturing the effects of health-aid and education independently, all the other covariates enter linearly.

Results

Table 2.3 reports the parametric and semiparametric regression estimates. As we see from Table 2.3, we do a parametric specification, and under the semiparametric specification we consider both an additive and a non-additive specification. We use different combinations of control variables in our estimations. We consider the specifications with/without the health aid-education interaction term. The interaction term

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[9] We consider the additive model specification since the cross partials between health-aid and education under the non-additive model specification turn out to be insignificant.

helps us examine if populations with higher primary completion rates (proxy for education) helps improve the effectiveness of health-aid. Checking for the sign and the significance of the coefficient of health aid-education interaction term in parametric

Table 2.3: Parametric and Semiparametric Estimation Results

	Parametric		Semiparametric	
Specifications	1	2	Non-additive	Additive
Health-aid	-1.70 (-0.69)	-1.35 (-1.29)	-0.001 (-0.19)	-0.22 (-0.15)
Education	-0.75 (-3.13)***	-0.72 (-11.54)***	-0.53 (-6.17)***	-0.47 (-4.18)***
Health-aid*Education	0.004 (0.16)		-0.00003 (-0.002)	
GDP per thousand	-11.47 (-7.27)***	-11.50 (-7.36)***	-10.87 (-7.58)***	-10.87 (-7.58)***
Physician	-0.60 (-0.33)	-0.62 (-0.34)	-2.26 (-1.22)	-2.26 (-1.22)
Population	-12.32 (-1.73)*	-12.41 (-1.75)*	-4.40 (-0.64)	-4.40 (-0.64)
Population^2	0.39 (1.74)*	0.39 (1.76)*	0.18 (0.82)	0.18 (0.82)
East Asia dummy	-8.28 (-2.01)**	-8.34 (-2.04)**	-8.34 (-2.10)**	-8.34 (-2.10)**
SSA dummy	15.72 (4.83)***	15.75 (4.86)***	17.39 (5.59)***	17.39 (5.59)***
Constant	424.23 (6.30)***	422.70 (6.35)***	282.30 (172.14)***	282.30 (172.14)***
t-stat is reported in the parentheses.				
*Significant at 10%. **Significant at 5%. ***Significant at 1%.				

Note: For health-aid and education variables, we obtain varying estimates for partial effects under the semiparametric specification. The above table reports average of the point-wise estimates of health-aid and education variable.

model is analogous to examining the second cross partial, i.e., $\frac{\partial^2 IMR}{\partial haid \partial edu}$ in the non-additive semiparametric model. This examines whether primary levels of education can make health-aid more effective in reducing the IMR or not. Recall that in our partially linear model, covariates other than health-aid and education enter linearly (with the inclusion of a variable population square), and, therefore, we obtain only one coefficient estimate for each of them.

In all our specifications we find GDP and education have the correct sign and significance. Physician stock and health-aid always have the correct sign but is never significant. The health aid-education interaction term (health-aid*education) in parametric specifications or the second cross partials in the non-additive semiparametric specification are not significant, implying that education does not improve the effectiveness of health-aid. The population variable has the wrong sign. However, the coefficients corresponding to both the population variables are significant only in the parametric specification. The regional dummies always have the expected sign and significance under both specifications.

Unlike the parametric estimates which are a global fit, our semiparametric estimates which are a local fit, allow us to obtain point-wise/ range wise varying estimates and thus enables us to examine the estimated partial effects or the second cross partials at various ranges of the sample. Note that none of the point-wise estimates of the second cross partial ($\frac{\partial^2 IMR}{\partial haid \partial edu}$) in the non-additive semiparametric model appears to be significant. This indicates that education does not improve the effectiveness of health-aid in reducing the IMR. It is also important to note that we tried to see if physician stock, the

other infrastructure variable can make health-aid effective or not. The interaction term for these two variables (in parametric model) or the second cross partials of these two variables (in the semiparametric model) never turn out to be significant. The results are not reported for brevity.

The non-additive semiparametric specification also helps us obtain the impact of education and health-aid on the IMR at different values of the health-aid and education variables. As reported in Table 2.3, in our non-additive specification the average of the semiparametric point-wise varying estimates of the partial effects for the education $\frac{\partial IMR}{\partial edu}$ turns out to be significant and that of health-aid $\frac{\partial IMR}{\partial haid}$ turns out to be insignificant (which is consistent with the parametric estimates).[10] Note that while almost all the point-wise coefficient estimates for education are negative and significant, only few of the point-wise estimates of the health-aid variable have the expected (negative) sign or significant.

In order to explain the health aid-education-IMR relationship in our non-additive specification in more detail, we present our point-wise estimates graphically in Figures 2.1–2.3. Note that these graphs are not plotting partial effects of heath-aid or education on the IMR. They are plotting the estimated health aid-education-IMR relation instead. However, the rising and the falling parts of these graphs (in the direction of health-aid or education axes) correspond to the positive and negative partial effects (of health-aid or

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[10] The corresponding point-wise estimates and their respective *t*-statistics for health-aid, education, and the interaction term at the median values for the non-additive semiparametric part are significant.

education), respectively. Figure 2.1 presents a three dimensional surface plot to describe estimated health-aid, education, and the IMR relation (after controlling for other covariates).[11] As expected, this graph indicates an overall decline in infant mortality as the education increases. However, the impact of health-aid on the IMR differs in various ranges of the data.

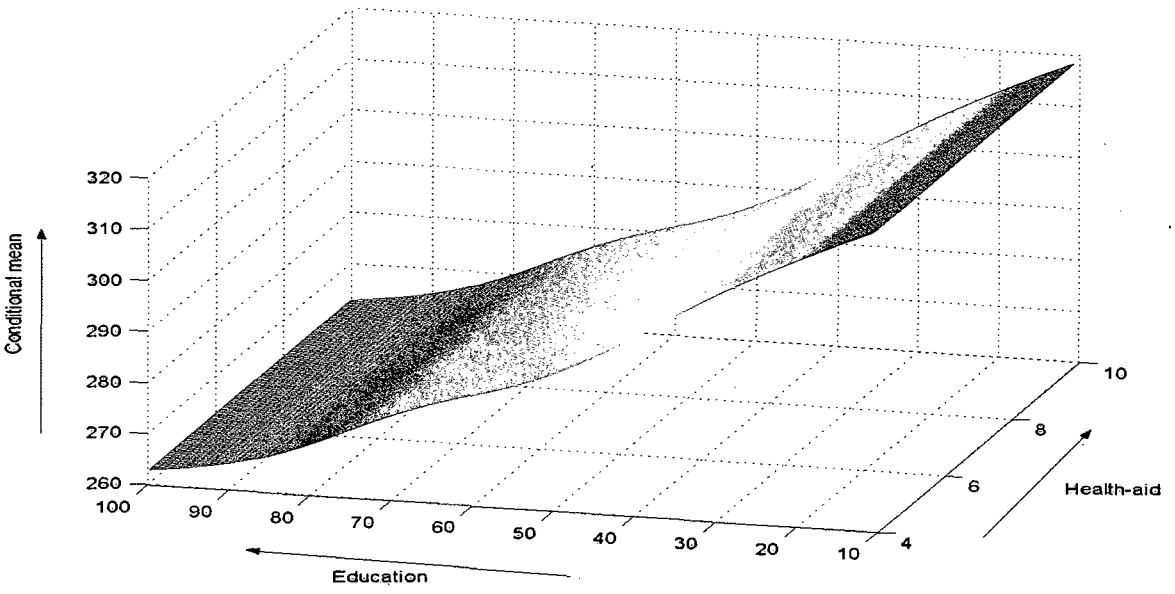

Figure 2.1: IMR-Health-aid-Education Relation

For a clearer understanding, we also slice the surface plot (Figure 2.1) in various ways, keeping the data points fixed at different quartile values of education or health-

[11] We have used twice of the optimal bandwidth in all these specifications. As a robustness check we also used optimal bandwidths and obtained similar results.

aid.[12] Figure 2.2 represents the slice of the surface plot at the median value of health-aid, which is 7.82 in log terms (approximately $2490). It looks at the estimated education-IMR relation at the median value of health-aid. As expected, the inverse relationship between education and the IMR is clearly seen in this plot. For this about 98% of the coefficients have the expected sign and 96% are significant. We observe similar patterns when we plot the same for the first and the third quartile values of health-aid.[13] Figure 2.3 represents the slice of the surface plot at the median value of education which is 61.12, thus focusing mainly on the estimated health aid-IMR relation. A similar pattern is also seen when we fix the education at its first quartile values; however, when we use the third

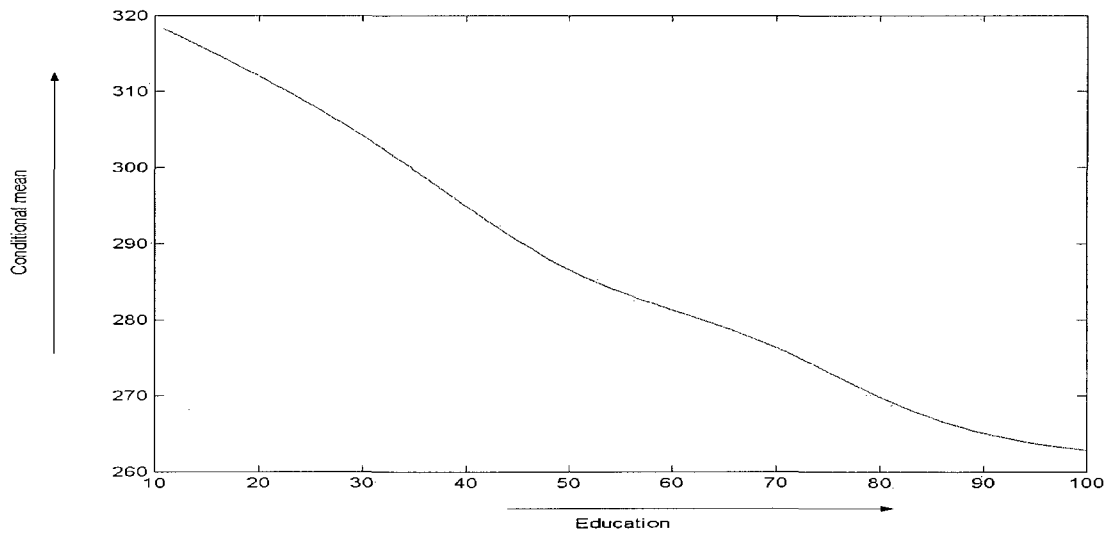

Figure 2.2: Education and IMR Relation at Median Values of Health-aid

[12] Only the slice of the plots corresponding to the median values of health-aid and education has been reported (Figure 2.2 and Figure 2.3, respectively).

[13] Such inverse pattern is not so clear in Figure 2.1, but the slicing of the plot (as in Figure 2.2) gives a clearer idea.

quartile values, the pattern changes to a positive relationship between health-aid and IMR, although almost all the health-aid coefficients in this range are insignificant.

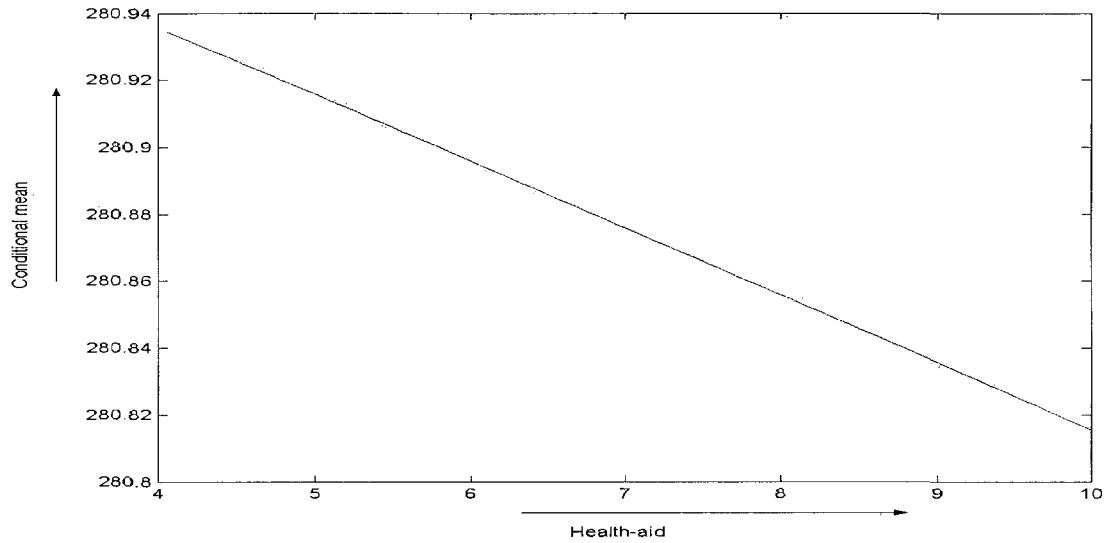

Figure 2.3: Health-aid and IMR Relation at Median Values of Education

It is to be noted that about 22% of the point-wise estimates of the partial effects are negative and significant as expected, whereas only 10% are actually positive and significant, implying a counterintuitive effect of health-aid on IMR. The rest of the estimates (associated with various ranges of the graph) are insignificant. Note that the average of the point-wise semiparametric coefficients turn out to be insignificant (as reported in Table 2.3) because these positive (and significant), negative (and significant) and insignificant coefficients average themselves out. In a linear parametric model, one reports only a single coefficient for any partial effect and, therefore, such detailed information remains unexplored and we find that the effect on an average is insignificant.

We also try a more generic specification by using an additive model and check if this improves our results.[14] This model specification allows us to check the impact of health-aid and education on IMR separately rather than considering their joint effects. In this model, as show in equation (2), where Y is the vector of dependent variable (IMR), X is the set of relevant macroeconomic covariates modeled linearly, β is the associated parametric vector and Z_1 and Z_2 correspond to the semiparametric variables, i.e., health-aid and education, which enter additively, $f(.)$ and $g(.)$ is the unspecified (nonparametric) functional form. The point-wise partial effects for health-aid and education help us know the ranges of the data for which they are significant. We continue to see that the average of the point-wise partial effects for the education variable are negative and significant and the health-aid variable remains negative and insignificant. To explain the effects of the health-aid and education variables, we plot them against their respective point-wise estimates. We also check the ranges for which health-aid and education are significant by plotting the partial effects at the 5% level. Figure 2.4 clearly indicates that the point-wise estimates of the partial effects corresponding to education variable are almost always (about 95% of the sample) negative and significant.[15]

The plot corresponding to the health-aid variable is shown by Figure 2.5. The plot clearly indicate that the partial effects for the health-aid variable move from positive (30% of the point-wise partial effects) to negative (70% of the point-wise partial effects)

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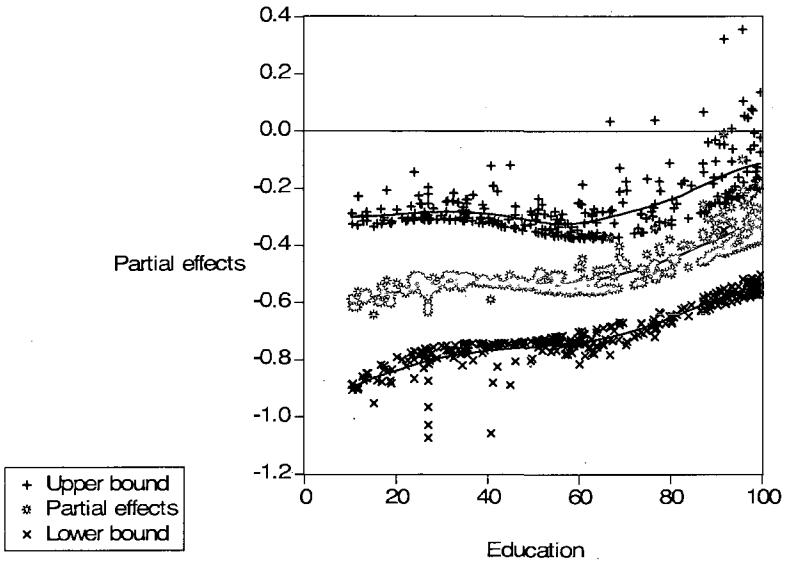
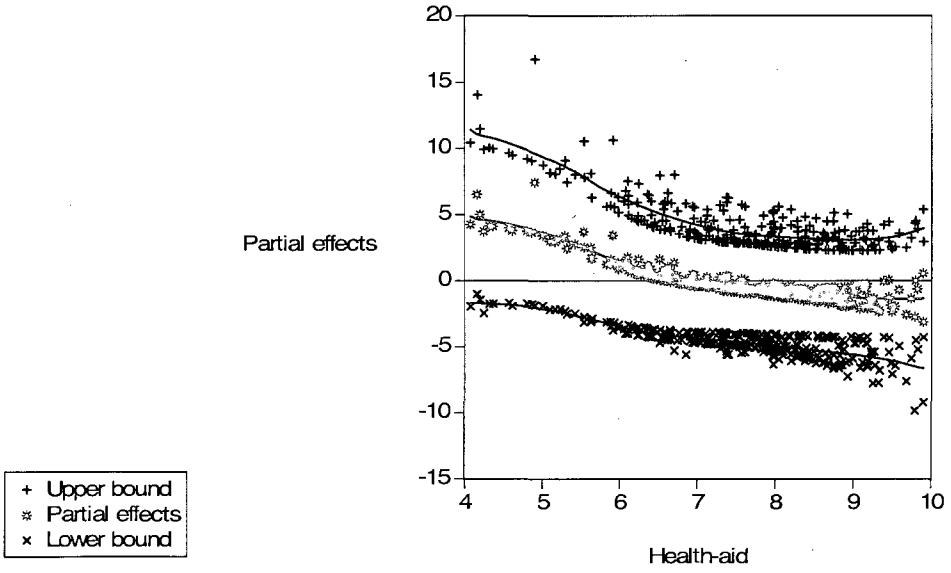
[14] We use NPREG [www.r.project.org; http://www.economics.mcmaster.ca/racine] to generate the coefficient values for health-aid and education through an additive model.

[15] In Figure 2.4, note that the since the zero line lies above the band, it indicates that the individual coefficients are significant.



Note: The zero line passing through the band indicates that the individual coefficients are insignificant

Figure 2.4: Partial Effects of Education with 5% Upper and Lower Bounds



Note: The zero line passing through the band indicates that the individual coefficients are insignificant

Figure 2.5: Partial Effects of Health-aid with 5% Upper and Lower Bounds

as the health-aid value increases. In fact, we see that after health-aid reaches a level of 6 (in log terms), i.e., about $403 the point-wise estimates turn negative from positive. However, since the zero line passes through the band, as shown in Figure 2.5, it indicates that the individual coefficients of the health-aid variable are insignificant. Thus we see that health-aid does have the correct sign beyond a threshold level, although the effect is never significant.

Conclusion

This chapter focuses on the impact of health-aid on a health indicator like the infant mortality rate. Instead of just considering a parametric fit, this chapter uses a semiparametric setting, which does not impose/assume any functional form for the relation of interest and hence avoids misspecification bias in the estimates. We use both a non-additive and an additive semiparametric specification. Our findings suggest that education and income always help lower IMR, but health-aid does not play much significant role. It may randomly benefit some countries during some time periods, but in general the effect of health-aid does not seem to be robust. We also find that health-aid is not effective at all if only a limited amount is given. The other interesting finding is that neither physician stock nor education can make health-aid more effective and physician stock by itself is not effective either. The policy implications of our findings are interesting. Both donors and recipient countries could direct a part of the funds toward meeting basic educational standards as it serves as an important pre-requisite in lowering IMR. Resources could be diverted to generate public *awareness* among parents on issues related to child care, nutrition, and other related aspects of child health. Also, donors need

to monitor closely the purpose for which health-aid is actually being used. Only such close scrutiny can reveal the reasons behind the prolonged failure of multilateral health-aid or aid in general.

CHAPTER III

THE EMPIRICS OF HEALTH-AID AND INFANT MORTALITY: A QUANTILE REGRESSION ANALYSIS

Introduction

In this chapter we continue to investigate the IMR-health aid relationship, although estimation-wise we take a very different route than in Chapter II. While in Chapter II we perform a semiparametric mean regression and investigate how health-aid affects IMR in *various ranges of health-aid,* here we perform a semiparametric quantile regression and examine how health-aid affects IMR at *various levels/quantiles of IMR.* Thus the core issue—investigation of health aid-IMR relationship—is the same in both chapters. Therefore, for a literature survey related to aid-IMR relation, please refer to Chapter II. To the best of our knowledge, this is the first study that attempts to explore the aforementioned relationship in a quantile regression framework. Quantile regression is a cutting-edge technique in econometrics that provides a comprehensive analysis of the conditional distribution of the response variable. In the process, we also examine the effects of other covariates, i.e., education, physician stock, GDP, population, and regional dummies on different groupings/quantiles of infant mortality rates. Quantile regression provides estimators of the conditional quantiles of the dependent variable as opposed to the conditional mean of the dependent variable. Thus, it gives a clear idea of the effects

of the regressors on different quantiles of the dependent variable as opposed to estimating the effects of the regressors on an *average*.[16] Another advantage of this estimation technique is that it is robust to the presence of outliers, which is often a problem with the data related to developing countries. We use both parametric and semiparametric quantile regression methods and also compare the results with those obtained from analogous parametric and semiparametric mean regressions.

Using an unbalanced panel consisting of 100 developing countries spanning the time period from 1974 to 2005, we find that in both our parametric and semiparametric quantile specifications education has a negative and significant impact at all quantiles of IMR and so does GDP. In our semiparametric specification, we do find that physician stock plays a crucial role in lowering infant deaths especially from the 75th percentile onwards, i.e., country groups with high levels of infant deaths. However, we do not find the health-aid to be effective. Thus, by using two different estimation strategies in Chapters II and III, we arrive at the conclusion that health-aid does not significantly lower IMR.

Data and Some Descriptive Statistics

Data

The data set in this chapter are the same as that in Chapter II, covering the same set of countries and time periods. However, in Chapter II, in order to take care of the

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[16] The classical linear regression analysis summarizes the *average* relationship between the outcome variable of interest and a set of regressors, based on the conditional mean function.

endogeneity of the health-aid variable, we use a one period lag of the variable, that is, our health-aid covariate is a predetermined regressor. In this chapter, however, the econometric techniques that we use call for instrumental variable type regression, where lag of health-aid is used as the instrument and current health-aid is used as the endogenous regressor. Thus both current and lagged aid (as opposed to only lagged aid) are needed, and in the process we lose some observations in this chapter (owing to some missing values of current period health-aid for some countries and years).

Some Descriptive Statistics

However, as Table 3.1 below shows, descriptive statistics of our variables are very much similar (in terms of range, mean, and variance) to those obtained in Chapter II.

Table 3.1: Sample Summary Statistics

Variable	Mean	Std. Dev.	Min	Max
IMR	75.39	41.25	7.70	191
Health-aid	7.47	1.35	2.04	11.70
GDP	17.67	1.06	15.93	20.64
Education	62.09	29.12	10.30	128.69
Physician	0.54	0.83	0.01	5.19
Population	16.06	1.70	11.50	20.99

Note: Like in Chapter II, GDP and Health-aid are per 1000 of the population and in constant 2005 U.S. dollars. Population, GDP, and Health-aid are in log terms. The number of physicians and IMR are also per 1000 of the population.[17]

[17] The list of countries used in the sample is given in Appendix B. The variables and data sources are described in detail in Appendix A of Chapter II.

Estimation Method and Statistical Tests

We use Koenkar and Bassett (1978), type quantile regression approach, which allows estimation of the entire distribution of the response variable conditional on any set of regressors, i.e., replacing the conditional mean by the conditional quantiles, which give a more complete picture of the underlying interrelations. In order to understand how the quantile regression approach differs from the standard mean regression approach, let us consider the following.

Consider a classical linear regression model, where $Y_i = X_i'\beta + u_i$ for $i = 1, \ldots\ldots\ldots, n$ and assume $E(u_i \mid X_i) = 0$, then $E(Y_i \mid X_i) = X_i'\beta$. The parameter vector can be estimated through least squares where $\hat{\beta} = \underset{\beta}{Min} \sum_i (Y_i - X_i'\beta)^2$. Thus in a linear mean regression we get one single value for the slope coefficient.

In the quantile setting we assume that $Y_i = X_i'\beta_\tau + u_{i,\tau}$ and not the expected value, but the $\tau - th$ quantile of the error term conditional on the regressors is zero, i.e., $Q_\tau(u_{i,\tau} \mid X_i) = 0$. Then the $\tau - th$ conditional quantile of Y_i with respect to X_i can be written as $Q_\tau(Y_i \mid X_i) = X_i'\beta_\tau$. Thus in general for any τ in the interval (0,1), the parameter vector β_τ can be estimated by the minimization problem stated below, see, for example, Koenker and Bassett (1978), Koenkar and Hallock (2001):

$$\underset{\beta_\tau}{Min} \sum_{Y_i \geq X_i'\beta_\tau} \tau \mid Y_i - X_i'\beta_\tau \mid + \sum_{Y_i < X_i'\beta_\tau} (1-\tau) \mid Y_i - X_i'\beta_\tau \mid \qquad (1)$$

where Y_i is the dependent variable, X_i is a kx1 vector of explanatory variables, β_τ is the coefficient vector and will differ depending on which particular quantile (τ) is being

estimated. Thus the quantile approach gives a more complete picture of the set as it computes several different regression curves corresponding to the various percentile points of the distributions. This approach is also robust against outliers of the regressand. Also, the issue of endogeneity is taken care of in both the estimations. First we use the parametric quantile regression as proposed by Arias, Hallock, and Sosa-Escudero (2001), and next we use the semiparametric quantile regression as proposed by Lee (2007), which are discussed below in detail.

The structural equations as in Arias et al. (2001) are

$$Y = X\beta(\tau) + Z_1\gamma(\tau) + U \quad (1)$$

$$X = Z\pi + V \quad (2)$$

Y is the response variable, X is the matrix of endogenous variables determined simultaneously with Y, $\gamma(\tau)$ is the vector of associated coefficients and Z_1 is the matrix of exogenous regressors. $Z=[Z_1, Z_2]$ is a matrix combining all the exogenous variables and the instruments (say Z_2) and U and V are vectors of *i.i.d* error terms. In the first stage we regress X on Z and get the projections for X (i.e., $\hat{X}$). In the second stage we perform the quantile regression of the response variable, i.e., Y on $\hat{X}$ and Z_1 .

The second estimation technique is a series based semiparametric quantile regression developed by Lee (2007). The method adjusts for endogeneity by adopting a control function approach and presents a two-step estimator that exploits the partially linear structure of the model. Formally the model can be stated as below:

$$Y = X\beta(\tau) + Z_1\gamma(\tau) + U \qquad (1')$$

$$X = Z\ \pi(\alpha) + V \qquad (2')$$

where $\pi(\alpha) \equiv [\pi_1(\alpha), \pi_2(\alpha)]$ is a vector of unknown parameters for some $0<\alpha<1$ and all the other symbols are defined in the same way as in (1) and (2). In the first step one constructs the estimated residuals $\hat{V}$ from the linear quantile regression of X on Z and in the second step one does the partially linear regression of Y on X, Z_1 and $\hat{V}$. $\beta(\tau)$ and $\gamma(\tau)$ are estimated by a linear $(\tau - th)$quantile regression whereas the regression of Y on $\hat{V}$ is performed by nonparametric series method. So it is essentially a partially linear or semiparametric approach.[18] This approach corrects for the endogeneity by adding estimates of V as an additional explanatory variable in $(1')$ and, therefore, can be viewed as a variant of control function approach.

Under both the parametric and semiparametric specifications, for identification purposes it is assumed that there is at least one component of Z that is not included in Z_1 and that this component has a non-zero coefficient. In both our specifications, IMR is the dependent variable. Health-aid is considered to be endogenous. We use the lag of health-aid as Z_2, the instrument. As argued by Dalgaard, Hansen, and Tarp (2004), the one period lag of aid serves as the best instrument for aid. The other exogenous covariates used are education, physician stock, population, population square, GDP, and

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[18] See Li and Racine (2007) for details on nonparametric or semiparametric series method.

the two regional dummies for East Asia and Pacific regions and Sub-Saharan Africa regions.[19]

The second estimation technique (Lee, 2007) differs from the first (Arias et al., 2001) in the following ways. First, while the first technique uses fitted values of the endogenous covariates (obtained from the first stage regression) in the second stage estimation, the second technique follows a control function approach, i.e., it uses the estimated residuals of the endogenous covariates (obtained from the first stage regression) in the second stage. Secondly, the first technique is a fully parametric one. But the second method uses a partially linear framework at the second stage regression. While assessing the effect of the estimated residual $\hat{V}$ on the response variable at the second stage, it uses a series based nonparametric modeling. The superiority of such modeling is established in Lee (2007). We try both the techniques, the first one as a benchmark or more standard approach, and the second one as a more novel approach and, to the best of our knowledge, the most recent approach in the literature of quantile regression with endogeneity. We then compare the results from both these regressions. Arias et al. (2001) type two stage quantile regression is compared to the standard 2SLS mean regression.[20] Lee (2007) type quantile regression is compared to a two stage

[19] We also consider the square term of population in order to check for diminishing effects.
[20] See Greene (2000) for details on 2SLS estimations.

semi/nonparametric mean regression similar to Su and Ullah (2008).[21] We also compare the results with the corresponding mean regression techniques.

Results

Table 3.2 reports the parametric quantile regressions and the standard two stage least squares (2SLS) estimates and Table 3.3 reports the semiparametric quantile regression estimates and the analogous two stage semiparametric mean regression estimates of Su and Ullah (2008) type.

We also present graphical illustrations of our results Figures 3.1–3.8. Figures 3.1 to 3.4 correspond to Arias et al. (2001) type parametric quantile regression estimates, while Figures 3.5 to 3.8 correspond to Lee (2007) type semiparametric quantile estimates. The corresponding mean regression estimates are also compared in the graphs. We plot 19 distinct quantile regression estimates for τ ranging from 0.05, 0.10 .....0.95 along with their confidence intervals for four of our continuous covariates, namely health-aid, GDP, education and physician stock. In each of the plots along the horizontal axis we measure the quantile or τ scale, while the vertical axis represents the effect of the respective covariate. The solid curves in Figures 3.1 to 3.4 correspond to the parametric

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[21] Su and Ullah (2008) also add $\hat{V}$ (obtained from the first stage regression) in the second stage regression. However while performing the mean regression of Y on $X, Z_1, \hat{V}$ at the second stage they use a fully nonparametric model. But in order to make our results comparable to Lee (2007), we use Robinson (1988) type partial linear model at the second stage. Also note that while Su and Ullah (2008) type semiparametric mean regression is based on simultaneous equation control function approach, Li and Stengos (1996) type semiparametric method is a single equation framework which allows some of the covariates to be predetermined.

Table 3.2: Parametric Quantile and 2SLS Mean Regression Estimation Results

Quantile	Q10	Q25	Q50	Q75	Q90	2SLS
Health-aid	-5.17* (-1.74)	-5.49** (-2.12)	-1.62 (0.64)	-4.86 (-1.16)	-7.62 (-1.00)	-3.78 (-1.51)
GDP	-13.80*** (-4.37)	-12.80*** (-5.40)	-11.98*** (-4.24)	-16.65*** (-4.28)	-18.92*** (-2.74)	-13.23*** (-5.73)
Education	-0.63*** (-6.30)	-0.67*** (-5.86)	-0.62*** (-5.74)	-0.56*** (-4.58)	-0.43** (-2.06)	-0.65*** (-8.61)
Physician	0.81 (0.39)	0.07 (0.04)	-3.11 (-1.33)	-2.79 (-0.81)	-5.68 (-0.96)	-1.73 (-0.79)
Population	-11.45 (-1.28)	-5.53 (-0.56)	-5.58 (-0.61)	-15.63 (-0.83)	0.18 (0.01)	-6.01 (-0.69)
Population^2	0.34 (1.29)	0.17 (0.57)	0.18 (0.64)	0.38 (0.68)	-0.18 (-0.26)	0.16 (0.57)
EAP	-13.39** (-2.36)	-15.23* (-1.92)	-10.38* (-1.80)	-10.85* (-1.67)	-12.94 (-1.50)	-9.97** (-2.07)
SSA	10.95** (2.13)	18.42*** (3.12)	17.85*** (2.73)	16.74** (2.07)	20.41** (2.25)	-16.47*** (4.18)
R square	0.53	0.59	0.59	0.53	0.46	0.79
t-stats are reported in the parentheses.						
*Significant at 10%. **Significant at 5%. ***Significant at 1%.						

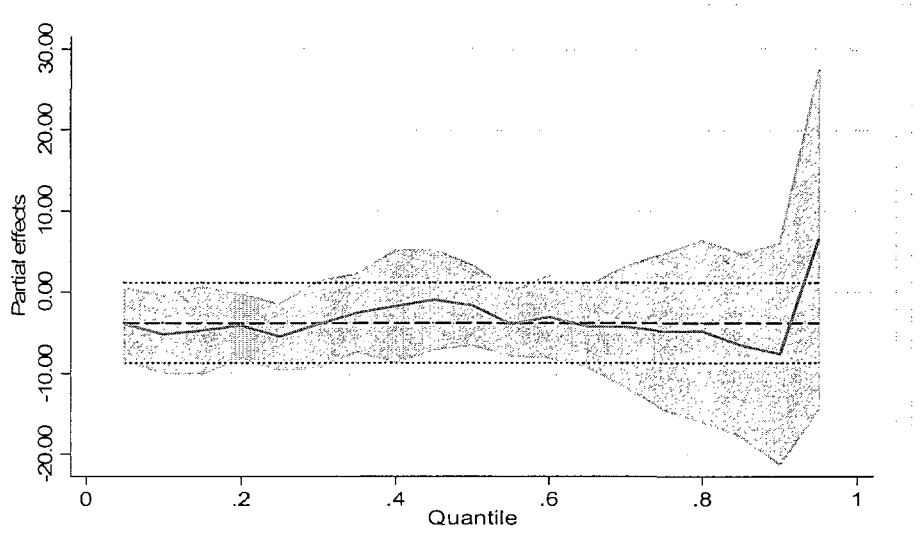
quantile estimates, while the shaded grey area represents the conventional 95% point wise confidence bands. In each graph, the horizontal dashed line represents point estimate from the corresponding mean regression and the two dotted lines represent their conventional 95% confidence intervals. Figures 3.5 to 3.8 present similar plots for the semiparametric regression estimates (quantile or mean).[22]

[22] It is obvious that as horizontal lines in all the graphs represent estimates from the mean regressions they do not vary across quantiles.

Table 3.3: Semiparametric Quantile and Two Stage Semiparametric Mean Estimation Results

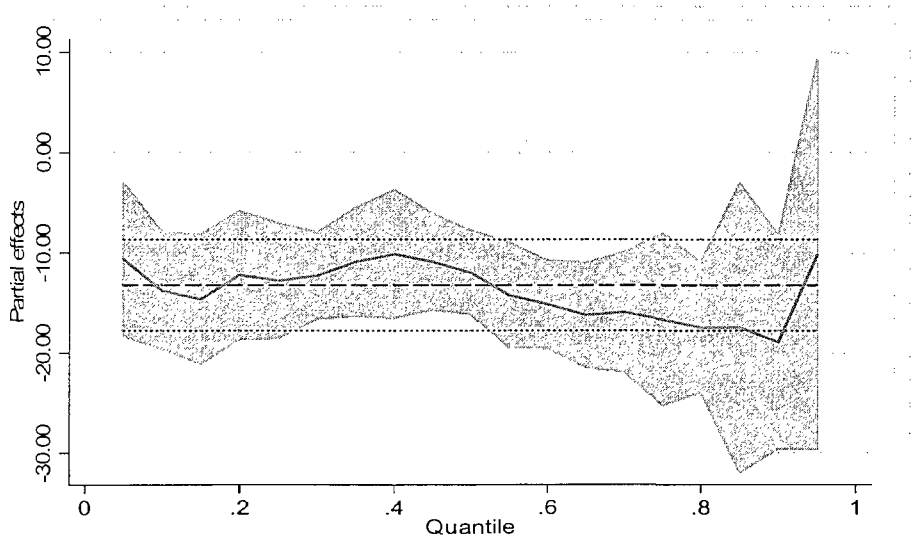
Quantile	Q10	Q25	Q50	Q75	Q90	Two Stage Semiparametric
Health-aid	-1.38 (-0.50)	0.51 (0.19)	3.03 (1.18)	4.51* (1.78)	-7.52 (-1.12)	-3.59 (-1.44)
GDP	-7.08*** (-2.72)	-7.31*** (-2.87)	-5.79** (-2.39)	-7.84*** (-3.40)	-10.46*** (-3.18)	-12.04*** (-5.36)
Education	-0.60*** (-4.59)	-0.70*** (-6.59)	-0.70*** (-5.90)	-0.66*** (-5.93)	-0.64*** (-4.77)	-0.69*** (-9.31)
Physician	2.29 (0.96)	3.18 (1.58)	0.21 (0.09)	-4.43* (-1.76)	-8.77** (-2.48)	-1.67 (-0.79)
Population	22.53*** (2.62)	22.13*** (2.84)	18.50** (2.38)	23.36*** (3.03)	49.58*** (3.36)	-4.08 (-0.48)
Population^2	-0.58* (-1.83)	-0.54** (-1.97)	-0.45 (-1.59)	-0.57** (-2.07)	-1.60*** (-2.95)	0.12 (0.43)
EAP	-13.52 (-1.51)	-6.00 (-0.82)	-9.14 (-1.60)	-21.71*** (-3.50)	-13.63 (-1.63)	-13.27*** (-2.75)
SSA	23.27*** (5.24)	27.05*** (5.79)	24.36*** (3.83)	12.48* (1.76)	12.50 (1.49)	16.47*** (4.30)
R square	0.78	0.82	0.75	0.81	0.77	0.79
t-stats are reported in the parentheses.						
*Significant at 10%. **Significant at 5%. ***Significant at 1%.						

From both the tables (Tables 3.2 and 3.3) and the graphs (Figures 3.1 to 3.8) we conclude the following. In both our parametric and semiparametric quantile regressions we find that education and GDP have negative and significant impacts across all quantiles of IMR. This implies that populations that have achieved higher levels of primary schooling completion rate (i.e., basic education) seem to help health indicators like IMR perform better. This could be attributed to factors like better awareness among parents on issues related to pre-natal and neo-natal care. Thus improving the quality of



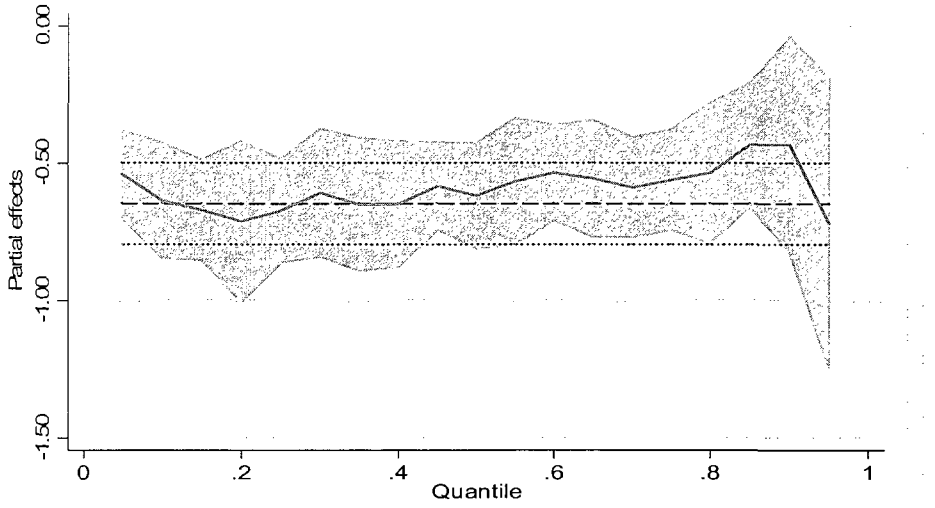
Note: The solid curve corresponds to the parametric quantile estimates for the different quantiles of IMR, and the shaded grey region represents their confidence intervals. The horizontal lines which represent the 2SLS point estimates and confidence intervals are indicated by the dotted lines.

Figure 3.1: Parametric Quantile Graph for Health-aid



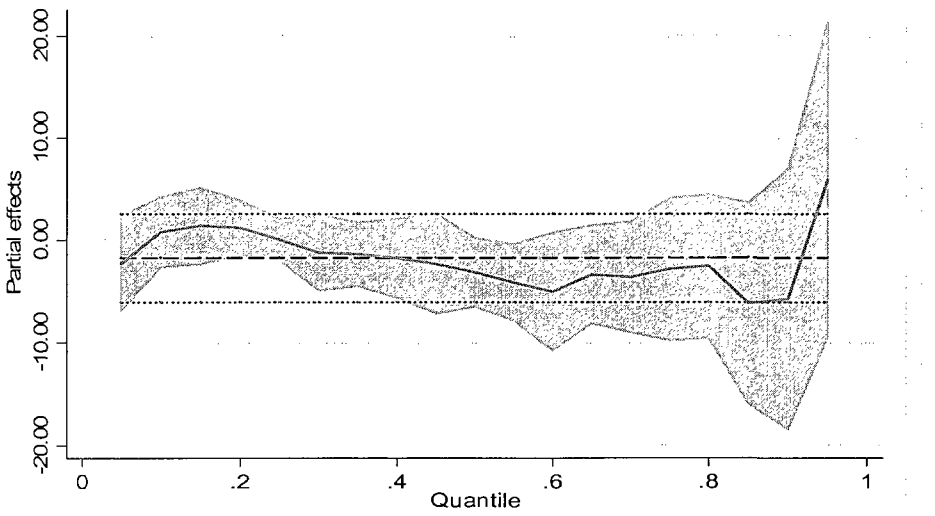
Note: The solid curve corresponds to the parametric quantile estimates for the different quantiles of IMR, and the shaded grey region represents their confidence intervals. The horizontal lines which represent the 2SLS point estimates and confidence intervals are indicated by the dotted lines.

Figure 3.2: Parametric Quantile Graph for Gross Domestic Product



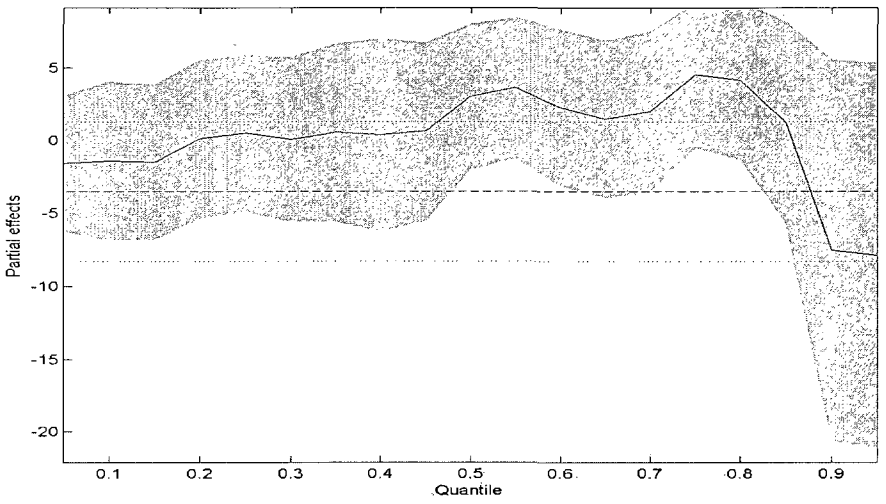
Note: The solid curve corresponds to the parametric quantile estimates for the different quantiles of IMR, and the shaded grey region represents their confidence intervals. The horizontal lines which represent the 2SLS point estimates and confidence intervals are indicated by the dotted lines.

Figure 3.3: Parametric Quantile Graph for Education



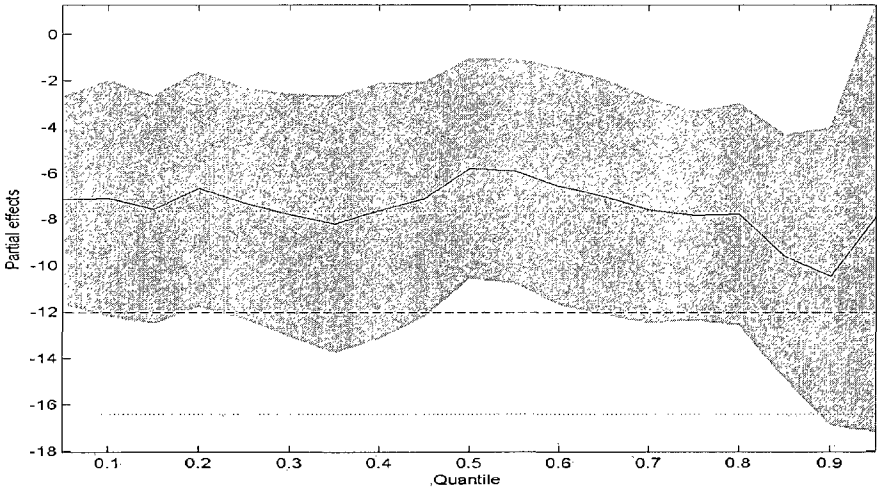
Note: The solid curve corresponds to the parametric quantile estimates for the different quantiles of IMR, and the shaded grey region represents their confidence intervals. The horizontal lines which represent the 2SLS point estimates and confidence intervals are indicated by the dotted lines.

Figure 3.4: Parametric Quantile Graph for Physician



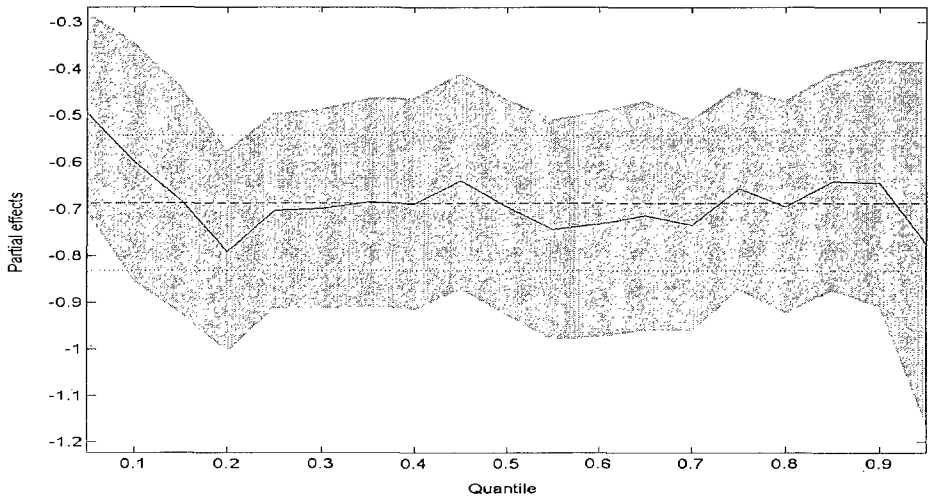
Note: The solid curve corresponds to the semiparametric quantile estimates for the different quantiles of IMR, and the shaded grey region represents their confidence intervals. The horizontal lines which represent the two stage semiparametric mean regression and their confidence intervals are indicated by the dotted lines.

Figure 3.5: Semiparametric Quantile Graph for Health-aid



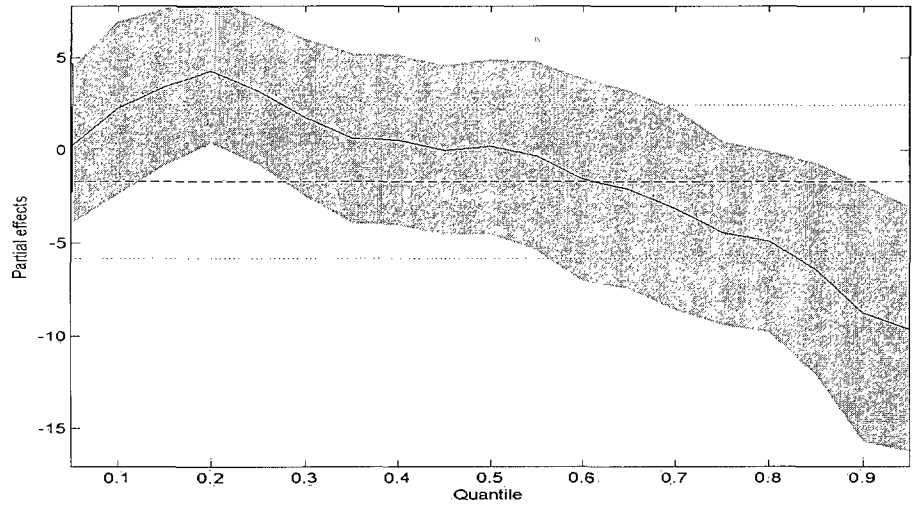
Note: The solid curve corresponds to the semiparametric quantile estimates for the different quantiles of IMR, and the shaded grey region represents their confidence intervals. The horizontal lines which represent the two stage semiparametric mean regression and their confidence intervals are indicated by the dotted lines.

Figure 3.6: Semiparametric Quantile Graph for Gross Domestic Product



Note: The solid curve corresponds to the semiparametric quantile estimates for the different quantiles of IMR, and the shaded grey region represents their confidence intervals. The horizontal lines which represent the two stage semiparametric mean regression and their confidence intervals are indicated by the dotted lines.

Figure 3.7: Semiparametric Quantile Graph for Education



Note: The solid curve corresponds to the semiparametric quantile estimates for the different quantiles of IMR, and the shaded grey region represents their confidence intervals. The horizontal lines which represent the two stage semiparametric mean regression and their confidence intervals are indicated by the dotted lines.

Figure 3.8: Semiparametric Quantile Graph for Physician

the human infrastructure helps improve health indicators further. Also, better earning capacities (income per capita) would, in turn, be reflected in more nutritious food intake and better health conditions, which would lower the risks of infant deaths. We also find that countries that belong to Sub-Saharan Africa are associated with significantly high IMR. The corresponding two stage estimations under both the parametric and semiparametric mean regression specifications also confirm these findings.

However, the conclusions corresponding to health-aid, physician stock, and the East Asian and Pacific regions are not uniform across the specifications. In our parametric quantile specification we find our health-aid variable to be significant in the lower quantiles of IMR.[23] This basically suggests that countries with already lower IMR have a further gain from health-aid, while countries with higher IMR do not seem to benefit from the health-aid, other things being held constant. That is, health-aid actually does not help significantly lower IMR among relatively poorer countries. However, in our semiparametric specification we do not find health-aid to be effective in any quantile of IMR. Note our semiparametric quantile specifications provide better goodness-of-fit (which is reflected in the R square values) than their parametric counterparts, suggesting that semiparametric quantile regressions (Lee, 2007) provide better predictions than the parametric quantile regressions (Arias et al., 2001). The overall parametric R square value is 0.5484, and the corresponding R square value in the semiparametric specification is 0.7857. Therefore, combining the results from the parametric and semiparametric

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[23] Health-aid is significant in three quantiles (10^{th}, 15^{th}, 25^{th}) details not reported, which implies that health-aid is effective at lower levels of IMR (or country groupings with lower levels of poverty).

quantile regressions, we conclude that there is *no robust* evidence that health-aid significantly lowers IMR in any quantile of IMR. Our analogous parametric and semiparametric mean regression estimates (as reported in the last columns of Tables 3.2 and 3.3) also conforms to our main conclusions—that education and GDP helps lowering IMR, but health-aid does not work. We also notice some other interesting findings in our semiparametric quantile regression. In this estimation we find physician stock has the desired negative and significant impact only after it crosses the 0.75^{th} quantile and thereafter is always significant (unlike the parametric quantile, where physician stock was significant only in the 0.55 and 0.60 quantiles of IMR). Another observation is that increases in population also seem to increase the incidences of IMR across the different quantiles but at a diminishing rate. Also, we find the East Asian and Pacific dummy to be mostly insignificant (except after the 0.75 quantile is reached), unlike the parametric quantile specification where it was mostly significant.

Conclusion

Despite the lack of robust empirical evidences of the effectiveness of overall aid in increasing economic growth, aid still continues to play an important role in developing economies. Over the recent decade, developing countries have witnessed/experienced shifts in the purpose for which aid is disbursed by donors. Though in both Chapters II and III we mainly focus on the health-aid-IMR relationship, we approach the issue in two different ways. In Chapter II, through a data-driven specification, we assessed the effectiveness of health-aid on the health outcome IMR at varies ranges of health-aid. The findings of our semiparametric estimation used in Chapter II indicated the ineffectiveness

of health-aid at all ranges of the health-aid variable. In the present chapter, we mainly focus on the impact of health-aid on IMR at different quantiles/ranges of IMR. We conclude that there is no robust evidence in favor of the effectiveness of health-aid in any of the quantiles of IMR. The parametric and semiparametric quantile regression estimations confirm that education and GDP have the desired significant impact in lowering IMR across all quantiles. We also find that countries belonging to the Sub-Saharan African regions are associated with high IMR in all the quantiles, and physician stock significantly lowers IMR in the quantiles above 0.75, i.e., it helps countries with relatively high IMR or high poverty levels.

The policy implications of our findings are interesting. Along with investing in the health-needs of developing economies, donors need to divert aid toward improving human infrastructure like basic education as well. Basic education would create the much needed awareness of better living conditions, child nutrition, and child care among the population. Higher income levels also help with proper child care and nutrition. Moreover, better monitoring of health-aid (the way it is being used presently) may also help find answers to the ineffectiveness of health-aid.

CHAPTER IV

HEALTH-AID AND INCIDENCE OF TUBERCULOSIS: AN EMPIRICAL ANALYSIS

Introduction

Over the decades developing countries have experienced a shift in both the amount and the purpose for which foreign aid is disbursed. The emphasis changed from "structural adjustments" in the 1980s to "conditionality" in 1990s. In the last decade, donor financing has been geared toward social services such as health and education (see Stevens, 2008). This is also oriented toward meeting the new global priority of the Millennium Development Goals (MDGs)[24]. The MDGs mainly emphasizes on improving human infrastructure.

In Chapter II we used a flexible functional form specification to see if health-aid affects health outcomes. The answer was negative. In Chapter III we use quantile regressions to examine if health-aid affects health outcome at any particular level of the health outcome variable. Again, our results witnessed the failure of health-aid. In both the chapters, we conclusively observed that the impact of education on health outcome is

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[24] The Millennium Development Goals (MDGs) are eight international development goals broken down into 21 quantifiable targets that are measured by 60 indicators. It was adopted by 189 nations and signed by 147 heads of state and governments. These goals respond to the world's development challenges and are agreed to be achieved by the year 2015. They include fighting infectious diseases such as tuberculosis, AIDS, etc., reducing child mortality, improving maternal health, reducing extreme poverty, developing a global partnership for development, to name a few.

significant. The question that comes next is "Can health-aid lower the incidences of infectious diseases?" In the present chapter, we examine if health-aid can lower a specific infectious disease, called tuberculosis—one of the most widespread infectious diseases in developing countries that results in a large number of deaths in the economically productive age group of 15-59 years. Following the growth-poverty literature, we used period average (of 4 years) in our previous chapters, since IMR was also a poverty indicator; however, in this study, since our dependent variable is not of a similar nature, we use annual level data, which leaves us with lot more time observations than in the previous chapters. In this chapter, therefore, we stick to the standard linear mean regression but explore the *dynamic nature* of the relationship in particular. We examine if by exploiting this dynamic nature we could find any significant impact of disaggregated health-aid on this specific infectious disease. Analogous to the growth literature, which uses an institutional quality index, we use primary schooling completion rate as a proxy to measure the human infrastructure, which is a key pre-requisite (similar to the earlier chapters) for improving health standards/outcomes of developing countries.

We use longitudinal data analysis methods on an unbalanced panel of 112 developing countries from 1990-2005. Our dynamic panel model specifications (differenced GMM and systems GMM) take care of issues like serial correlation, country specific heterogeneity, and endogeneity. Our results confirm that among the covariates considered education does play an important role in lowering the incidences of infectious diseases. We also find there is a significant lagged effect of the incidences of tuberculosis, which basically supports the contagious nature of the disease. Interestingly, in this analysis too we find the effect of health-aid to be always insignificant.

Literature Review

Existing literature examining the effect of aid on infectious diseases in particular is rather limited. Thiele, Nunnenkamp, and Dreher (2007) use a Tobit regression analysis to test if sectorally disaggregated data on aid-by-purpose (given by various bilateral and multilateral donors) do have any significant impact on meeting Millennium Development Goals for a sample of 140 recipient countries for the period of 2002-2004. The study also examines whether the donors allocated aid is in accordance with the sector specific needs of recipient countries. For example, Millennium Development Goals suggests that aid should be targeted at reducing incidences of infectious diseases. The findings indicate that while aid targeting has been effective in fighting infectious diseases like HIV/AIDS, it has not helped lower incidences of tuberculosis or malaria, nor has it helped increase primary education levels. They attribute part of this failure to insufficient targeting of aid, where donors focus on some MDG targets, neglecting the other ones. Momota, Tabata, and Futagami (2005) use a two period overlapping generations model, which reveals the cyclical nature of infectious diseases and also conclude that a one time foreign aid would not be helpful. Martin, Rice, and Smith (2008) use health care data developed by the English National Health Services (a publically funded health system) to assess the link between health care spending and health outcomes. Their findings suggest that health care spending can improve certain specific health outcomes like cancer and circulation in particular. Both Shiffman (2006) and Landis (2005) examine donor funding priorities to the burden of diseases in recipient countries. Shiffman's study indicates that funding (provided by bilateral donors, international financial institutions like the World Bank and others) does not correspond to the burden of the disease and concluded that fundings

toward infectious diseases like respiratory infections and malaria are highly insufficient. Landis looks at development assistance for all diseases and concludes that while health areas like basic health-care and infrastructure, health education and personnel development, etc., have witnessed a decline in allocations, infectious diseases and HIV/AIDS have received larger share of resources/ funding. Both papers conclude that the funding patterns do not necessarily mirror the needs of developing world. Though the literature is limited, some of the above discussed papers mainly do focus on aid *disbursement* toward disease control. In the light of the above papers, this chapter empirically examines the *effectiveness* of health-aid on a particular infectious disease like tuberculosis in a rigorous manner.

Data and Some Descriptive Statistics

Data

Our sample covers 112 developing countries[25] spanning from 1990 to 2005; thus we have a total of 16 years. For this chapter we use annual level data, which give us a lot more time period observations than we had in the previous chapters. The number of observations varies across specifications depending on the control variables used. The dependent variable is the incidence of tuberculosis per 1000 of the population. The independent variables are GDP per 1000 of the population measured in constant 2005 U.S. dollars, primary schooling completion rate, density per square kilometer,

[25] Refer to Appendix C to see the sample of countries used in the analysis.

government health expenditure per 1000 of the population measured in constant 2005 U.S. dollars, the GINI index, health-aid per 1000 of the population measured in constant 2005 U.S. dollars, and the number of physicians per 1000 people. Note that primary schooling completion rate is used as a proxy for education and existing human infrastructure and physician stock is a proxy measure for existing health infrastructure. The GINI index measures the level of income inequality, which may lead to further deterioration of health outcomes. We also consider some period dummies to check if the implementation of the Millennium Development Goals or the changes in donor financing toward health-related issues have had a significant impact in lowering the incidences of tuberculosis. The health-aid^2 term is considered in order to check for the diminishing effects of health-aid. Interacting the health-aid term with physician stock or government health expenditure also helps us check if the existing amounts of physician stock or government health expenditure does improve the effectiveness of health-aid in reducing the incidences of tuberculosis.

Health-aid, as mentioned in the Chapters II and III, continues to be our most important covariate of interest. Ideally one would use the component of health-aid that is disbursed specifically for tuberculosis control. However, due to the lack of data at such disaggregated level, our best approximation is to use data on health-aid, i.e., aid that is directed toward health outcomes (same as defined in the earlier chapters).[26] The list of

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[26] The description of our Health-aid variable can be found in Appendix A of Chapter II. Although OECD does report data on the component of health-aid that is geared toward tuberculosis control, there are too many missing observations at this disaggregated level of aid, which prevents us from doing any meaningful regression analysis with such data.

variables and data sources can be found in Appendix C. Note in our previous chapters following the growth-poverty literature, we took period average since IMR is also a poverty indicator. Since our dependent variable (incidences of tuberculosis) is not of a similar nature, we use annual data, which leaves us with a lot more time observations to explore. Hence we can examine the dynamic nature of the interrelationship between health-aid and incidences of tuberculosis.

Some Descriptive Statistics

Table 4.1 represents the summary statistics. On an average there are about 2 incidences of tuberculosis that are reported per 1000 of the population per year. The incidence of tuberculosis in Swaziland is as high as 11 cases per 1000 of the population in comparison to developed countries like Sweden and Canada with about 5 or 6 cases. The availability of physicians on an average is as low as 0.66 per 1000 of the population. We also see governments of developing economies spend a substantial amount on the health needs of the population. The GINI index measures inequality in income distribution is expressed in percentage terms. The higher the percentage value, the greater the level of inequality. The average density is about 106 people per square kilometer. The average primary completion rate is about 66%. On an average about $1280 (in constant 2005 U.S. dollar per year) of health-aid is disbursed per 1000 of the population.

The region wise spread of the incidences of tuberculosis across time is shown in Table 4.2. The figures indicate a drop over the previous period in the incidences of tuberculosis for East Asia and Pacific, Latin America and Caribbean, Middle East and North Africa, and South Asia. There has been an increase in the incidence of

tuberculosis, however, for Europe and Central Asia and Sub-Saharan Africa. This impact is reflected in the incidence of tuberculosis at the world level.

Table 4.1: Sample Summary Statistics

Variable	Mean	Std. Dev.	Min	Max
Tuberculosis	2.26	1.84	0.05	11.41
Government Health Expenditure	15.15	1.18	12.51	18.01
Physician	0.66	0.93	0.01	7.88
Health-aid	7.16	1.62	1.45	12.59
Density	3.88	1.33	0.42	7.07
GDP	17.91	1.08	15.89	21.13
Education	65.79	28.37	10.78	143.67
GINI	43.37	8.00	28.15	62.35

Note: Government Health expenditure, Health-aid, GDP are all in constant 2005 U.S. dollar per year terms and per 1000 of the population. Density, Health-aid, GDP and Government Health expenditure are in log terms.

Table 4.2: Incidences of Tuberculosis by Regions of the World per 1000 of the Population

Regions	1990	1995	2000	2005
East Asia & Pacific	1.605434	1.518573	1.437496	1.365069
Europe & Central Asia	0.496378	0.622764	0.8365	0.814506
Latin America & Caribbean	1.009697	0.835699	0.696422	0.5859
Middle East & North Africa	0.543135	0.554058	0.49601	0.434136
South Asia	1.793714	1.781005	1.760692	1.741353
Sub-Saharan Africa	1.707991	2.356615	3.233816	3.730555
World	1.242278	1.278446	1.358767	1.394867

Source: WDI

Table 4.3 indicates the government health expenditure per 1000 of the population. The figures are in constant 2005 U.S. dollars. It clearly indicates an increased amount of spending by the government toward health needs of the population across all regions and the world at large.

Table 4.3: Government Health Expenditure per 1000 of the Population

Regions	2001	2002	2003	2004	2005
East Asia & Pacific	3790672	4293983	5154650	5954352	6939993
Europe & Central Asia	10742044	12961418	16004303	20273313	26170680
Latin America & Caribbean	23860648	20564217	21617975	25924982	32728020
Middle East & North Africa	6823586	7803696	7973459	9713890	12136970
South Asia	1685840	1804472	2152486	2532247	3091667
Sub-Saharan Africa	2653997	2735022	3421192	4246521	4925348
World	44363133	47868122	55188452	62328991	68614160

Source: WDI

It is also important to know how much of the amount of Official Development Assistance (ODA) that is disbursed toward the health sector needs of developing economies goes toward infectious disease control. Table 4.4 gives us the ODA provided between 1995 and 2005 that specifically goes toward the health sectors and for infectious disease control. The figures are in constant 2005 U.S. dollar terms.

A plot of the above table has been shown in Figure 4.1. It clearly indicates an increase in both overall health-aid disbursements and in the amounts of health-aid going toward infectious disease control over the 1995 to 2005 time frame.

Table 4.5 indicates the total level of health-aid disbursed to developing countries going specifically toward infectious disease control and tuberculosis control. The figures

Table 4.4: Total Health-aid and Health-aid Toward Infectious Disease Control

Year	Health-aid	Infectious Disease Control
1995	169062.6	7394.43
2000	139231.6	43030.29
2005	344805	112587.1

Source: OECD.Stat

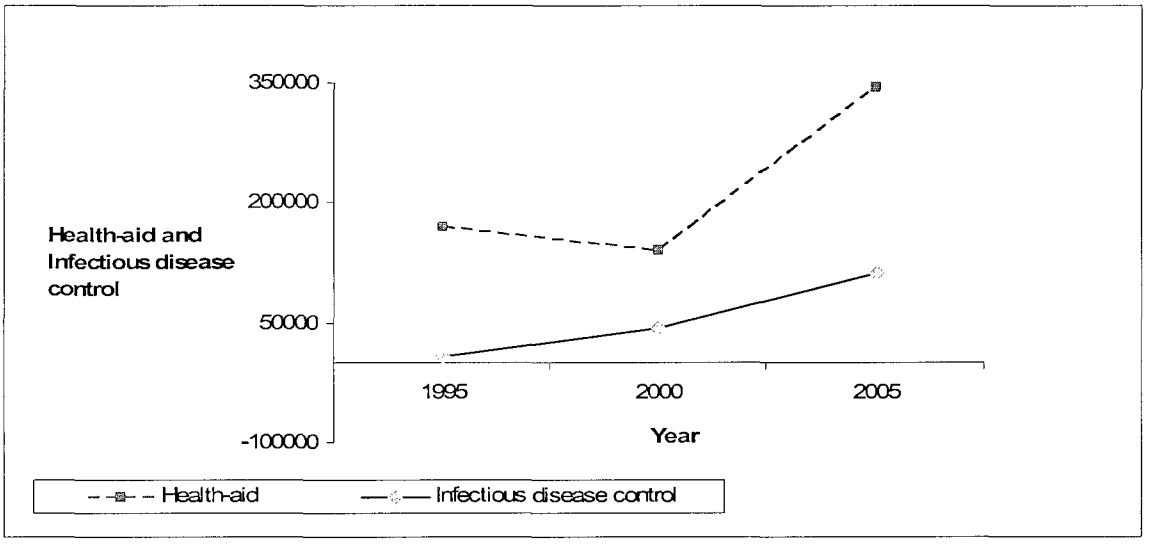

Figure 4.1: Trends in Foreign Aid Disbursements Allocated Toward the Health Sectors

Table 4.5: Trends in Health-aid Disbursement

Year	Infectious Disease Control	Tuberculosis Control	Share (%)
2003	71291.57	13825.14	19.39239
2004	66532.17	11057.25	16.6194
2005	112587.1	17914.55	15.91173

Source: OECD.Stat

are in constant 2005 U.S. dollars, though in actual terms there has been a continuous increase in the health-aid disbursement toward infectious disease control (except in the year 2004). The share of health-aid disbursed specifically toward tuberculosis control shows a less than 3% drop in 2004 from the previous year. The graphical representation is shown in Figure 4.2.

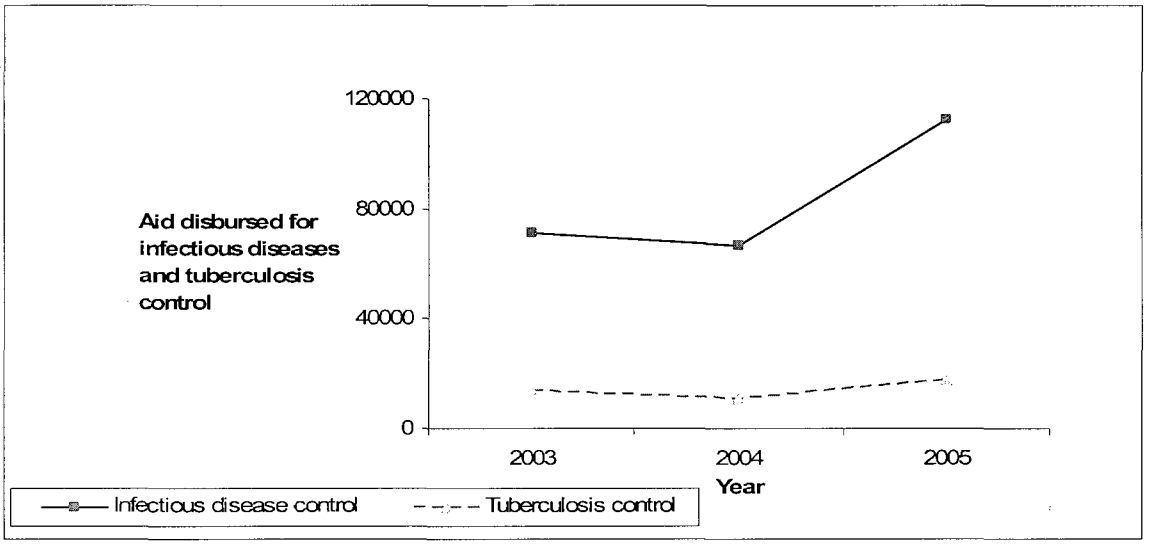

Figure 4.2: Trends in Health-aid Disbursements Toward Infectious Diseases

Estimation Method and Statistical Tests

This section describes the econometric technique we use for estimation purposes. Given the longitudinal nature of our data set, we applied panel data estimations techniques. We used Arellano and Bond (1991) differenced GMM and the system GMM estimators proposed by Arellano and Bover (1995) and Blundell and Bond (1998, 2000) while examining the effect of our main variable of interest (health-aid) on incidences of tuberculosis, after controlling for other covariates.

The general specification for a dynamic panel model is as follows:

$$Y_{it} = \alpha_i + \delta Y_{it-1} + X_{it}'\beta_k + u_{it} \quad (1)$$

Here Y_{it} is the dependent variable (incidences of tuberculosis per 1000 of the population) for country i at time t. X_{it} are the set of relevant macroeconomic covariates such as health-aid per 1000 of the population, government health expenditure per 1000 of the population, gross domestic product per 1000 of the population, education, physician stock per 1000 of the population, density per square kilometer, the GINI index, interaction terms and period dummies. β is the $k \times 1$ parameter vector associated with the independent variables defined above, α_i is the individual country specific effects which is considered to be constant over time t and is specific to individual units (see, for example, Greene, 2000), and u_{it} is the *i.i.d* error term. α_i is allowed to be fixed (nonstochastic) or random (stochastic).The presence of α_i along with the lagged dependent variable makes standard estimators inconsistent. Instrumental variable methods are used to resolve this issue where past values of the lagged dependent variable are uses as instruments (see Anderson and Hsiao, 1981). Arellano and Bond (1991) argue that a more efficient estimator, however, can result from the use of (additional) instruments whose validity are based on the orthogonality between all possible lagged

values of the dependent variable Y_{it} and the error u_{it}.[27] Taking $t = 3$ as the first period we can rewrite the relationship in (1) as $(Y_{i3} - Y_{i2}) = \delta(Y_{i2} - Y_{i1}) + (X_{i3} - X_{i2})'\beta + (u_{i3} - u_{i2})$. Y_{i1} is a valid instrument for $(Y_{i2} - Y_{i1})$, since these are highly correlated, and Y_{i1} is not correlated with $(u_{i3} - u_{i2})$ as long as u_{it} are second order serially uncorrelated. At $t = 4$ the relationship becomes $(Y_{i4} - Y_{i3}) = \delta(Y_{i3} - Y_{i2}) + (X_{i4} - X_{i3})'\beta + (u_{i4} - u_{i3})$. Here Y_{i2} and Y_{i1} are both valid instruments, uncorrelated with $(u_{i4} - u_{i3})$ as long as u_{it} are second order serially uncorrelated. Thus proceeding in this manner $(Y_{i1}, Y_{i2}, Y_{i3}.....,Y_{iT-2})$ can serve as valid instruments if the relationship is $(Y_{it} - Y_{it-1}) = \delta(Y_{it-1} - Y_{it-2}) + (X_{it} - X_{it-1})'\beta + (u_{it} - u_{it-1})$. Including the other covariates we can see that at T, the valid set of instruments can possibly be $(Y_{i1}, Y_{i2}, Y_{i3}.....,Y_{iT-2}, X_{i1}, X_{i2}, X_{i3}, ..., X_{iT-1})$. Arellano and Bond propose consistent generalized method-of-moments (GMM) estimator for the parameters of this model. We used two step estimators as it is more efficient than the one step estimator.

We conducted two important tests that help us check for the validity of the GMM estimators. The first is the autocorrelation test where the null hypothesis is no second-order serial correlation in the error term of the first-differenced equation: it requires $E[\Delta u_{it} \Delta u_{it-2}] = 0$. Another test for the validity of the instruments is Sargan's (1958) test of over-identifying restrictions: it requires $E[W'\Delta u] = 0$, i.e., the instruments are

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[27] Anderson and Hsiao (1981) (first differenced) instrumental variables estimator do not take into account all the available moment restrictions; thus though consistent, they are not as efficient as Arellano and Bond (1991).

uncorrelated with first difference errors; where W is the instrument matrix, and Δu is the vector of first differenced errors; see Arellano and Bond (1991) for details. If the null hypothesis is rejected, it implies that we either have to reduce the number of instruments or have to find a more appropriate set of instruments. Thus in both the tests we need to accept the null hypothesis in order to use the Arellano Bond estimator.

We also apply the systems GMM estimation technique to improve efficiency, increase precision, and reduce finite sample bias of the standard first differenced GMM estimators (see, for details, Baltagi, 2005). It was first introduced by Arellano and Bover (1995) and also developed by Blundell and Bond (1998, 2000). The approach imposes additional restrictions on the initial conditions which can be exploited by a system of first differenced and level equations, thereby improving the efficiency of the standard first differenced estimator. See Arellano Bond (1995) and Blundell and Bond (1998, 2000) for details. To understand this method let us consider the model as in (1)

and rewrite $\varepsilon_{it} = \alpha_i + u_{it}$. (2)

The first difference of (1) is $\Delta Y_{it} = \delta \Delta Y_{it-1} + \Delta X_{it}' \beta_k + \Delta u_{it}$ (3)

The moment conditions in the first difference equation are $E(Y_{i,t-s} \Delta u_{it}) = 0$ for $t = 3 \ldots\ldots T$ and $2 \le s \le T-1$. The moment conditions for the level equation are $E(u_{i,t-s} \Delta Y_{it}) = 0$. Thus this specification uses more moment conditions—lagged differences are used as instrument for level equation and lagged levels are used as instruments for difference equation. The condition for no second order serial correlation is $E[\Delta u_{it} \Delta u_{it-2}] = 0$. The consistency of system GMM estimators depends on the

validity of instruments and the absence of second order serial autocorrelation. Details of the various estimation results follow.

Results

Table 4.6 reports the coefficient estimates for the Arellano Bond (1991) Generalized Method of Moments (GMM) estimation.

As we see from this table, in most of our specifications the covariates turn out to be insignificant. We find aid to be ineffective and in some cases it also has the wrong sign. The lagged value of our dependent variable is positive and significant in the last specification, thereby supporting the contagious nature of the disease. We do find support for the fact that primary levels of education do lower the incidences of tuberculosis. However, as mentioned earlier, the results of our systems GMM estimation procedure are more efficient and precise; hence we rely more on the results of it than the standard first differenced GMM.

Table 4.7 reports the result of the systems GMM estimation procedure. As we see from this table, in all our specifications the lagged values of our dependent variable turn out to be positive and significant; which supports the contagious nature of a communicable disease like tuberculosis. We also find that the education variable turns out to be negative and significant in all our system GMM specifications. Thus given the basic nature of the disease (communicable), basic levels of education can substantially help lower the incidences of tuberculosis. This could be attributed to factors like better awareness of the nature of the disease, and better understanding of detection and prevention measures that could help avoid the possible spread of infectious diseases (for

Table 4.6: Dynamic Panel Estimation (Differenced GMM Estimation)

Specifications	1	2	3	4	5
Tuberculosis (Lag 1)	0.14 (0.22)	0.32 (0.57)	0.11 (0.23)	-0.08 (-0.20)	0.76*** (12.54)
Physician	0.01 (0.25)	0.01 (0.29)	-0.14 (-0.84)	0.01 (0.19)	-0.05 (-0.77)
GDP	0.05 (0.07)	0.02 (0.06)	0.27 (0.40)		-0.03 (-1.20)
GINI	-0.004 (-0.31)	0.01 (0.50)	0.01 (0.37)	-0.004 (-0.46)	
Density		-0.69 (-0.56)			
Education	-0.01 (-1.51)	-0.002 (-0.64)	-0.01 (-0.75)	-0.01*** (-2.60)	-0.003 (-1.09)
Education^2					0.00002 (0.99)
Health-aid (Lag1)	-0.001 (-0.04)	-0.01 (-0.38)	-0.27 (-0.45)	0.34 (1.14)	0.02** (2.00)
Health-aid^2 (Lag 1)			0.02 (0.45)		
Govt.Health Expenditure (Lag 1)	-0.12 (-0.21)	-0.21 (-0.75)	-0.23 (-0.72)	-0.20 (-1.03)	
Health-aid*Physician (Lag 1)			-0.01 (-0.29)		-0.01 (-1.39)
Health-aid*Govt.Health Expenditure (Lag 1)				-0.02 (-1.15)	
Yr 1995					-0.02 (-0.95)
Yr 2000					-0.01 (-1.25)
Yr 2003	-0.01 (-0.36)	-0.004 (-0.20)	0.01 (0.46)	0.002 (0.12)	
Yr 2005	-0.01 (-0.23)	-0.01 (-0.16)	-0.10 (-1.05)	0.01 (0.16)	-0.02 (-1.51)
Constant	2.26 (1.18)	4.95 (0.92)	3.81 (0.87)	3.47 (1.00)	1.17** (2.37)
No. of observations	55	55	55	55	436
No of panels	30	30	30	30	88
No. of instruments	15	16	21	18	48
Sargan	0.0751	0.10	0.5079	0.3631	0.4086
2Order Autocorrelation	0.7754	0.5663	0.5443	0.5619	0.10
t-statistics are reported in the parentheses.					
*Significant at 10%. **Significant at 5%. ***Significant at 1%.					

Note: We have reported the two step robust estimator coefficients in the above table; this is the WC-robust estimators of Windmeijer (2005). The *p* values corresponding to the Sargan test and the Second order autocorrelation tests are reported above.

Table 4.7: Systems GMM Estimation

Specifications	1	2	3	4	5
Tuberculosis (Lag 1)	0.97*** (14.92)	0.88*** (11.73)	0.98*** (26.18)	0.94*** (23.62)	1.09*** (49.58)
Physician	0.02 (0.85)	-0.02 (-0.61)	0.02 (0.31)	0.03 (1.05)	0.01 (0.03)
GDP	-0.09 (-0.75)	-0.06 (-0.38)	-0.07 (-0.71)		-0.07* (-1.92)
GINI	0.001 (0.35)	-0.001 (-0.25)	0.003 (0.70)	0.003 (0.79)	
Density		-0.04 (-0.61)			
Education	-0.004** (-2.22)	-0.004* (-1.90)	-0.003* (-1.67)	-0.003* (-1.89)	-0.004 (-1.34)
Education^2					0.00003 (1.19)
Health-aid (Lag1)	-0.01 (-0.51)	0.002 (0.14)	0.06 (0.60)	0.20 (1.63)	-0.02 (-0.86)
Health-aid^2 (Lag 1)			-0.01 (-0.73)		
Govt.Health Expenditure (Lag 1)	-0.12 (-0.67)	-0.18 (-1.19)	0.01 (0.06)	0.02 (0.18)	
Health-aid*Physician (Lag 1)			0.001 (0.15)		-0.01 (-1.35)
Health-aid*Govt.Health Expenditure (Lag 1)				-0.01* (-1.72)	
Yr 1995					-0.01 (-0.49)
Yr 2000					0.08** (2.21)
Yr 2003	-0.002 (-0.23)	-0.001 (-0.12)	-0.001 (-0.09)	-0.002 (-0.16)	
Yr 2005	0.03 (0.85)	0.04 (0.67)	0.02 (0.50)	0.01 (0.56)	-0.05** (2.11)
Constant	1.71 (1.22)	2.38 (1.09)	1.65 (1.29)	-0.99 (-0.46)	1.58** (2.21)
No. of observations	101	101	101	101	563
No of panels	45	45	45	45	95
No. of instruments	25	26	39	31	88
Sargan	0.8606	0.8173	0.7169	0.8532	0.6414
2Order Autocorrelation	0.6879	0.5410	0.9099	0.5810	0.1587
t-statistics are reported in the parentheses.					
*Significant at 10%. **Significant at 5%. ***Significant at 1%.					

Note: We have reported the two step robust estimator coefficients in the above table. The *p* values corresponding to the Sargan test and the Second order autocorrelation tests have been reported in the table.

etc.). Also, improving the nutritional intake and the living conditions (hygiene and sanitary conditions) could help improve health outcomes. Education thus acts as a pre-requisite in laying the foundation for an improved healthy lifestyle and also helps the productive ages to perform better, which will have a direct impact on their earning capacities. The complementarity between health-aid and government health expenditure seen in our fourth specification in Table 4.7 indicates the need for greater coordinated efforts between the donor countries and recipient governments. In our last specification we also find some of the period dummies and GDP to have significant impacts. Thus the overall conclusion of the systems GMM confirms that health-aid by itself does not help lower the incidences of tuberculosis. Government efforts may help in improving health outcomes along with health-aid but not by itself. We do find primary completion rate helps lower the incidences of tuberculosis across all systems GMM specifications.

Conclusion

The policy implications of this chapter are interesting. Donors could channelize some of the funds toward developing the human infrastructure and systems strengthening (health infrastructure). Also, more coordinated efforts between donors and the recipient countries are called for. The failure of health-aid by itself could be attributed to various factors. The weak health systems among developing countries can be considered as an important factor behind the ineffectiveness of health-aid. Lack of coordinated efforts on the part of the donor countries and the recipient economies in meeting desired goals could also be another factor. As found in the literature, one could also attribute the cause of ineffectiveness to insufficient targeting by donors to specific diseases; see Thiele et al.

(2007) Shiffman (2006), and Landis (2005), to name a few. From the policy perspective, aid could be diverted toward strengthening the basic system (by investing in health infrastructure and human infrastructure). Donors could also indulge in more purposeful aid targeting. Since by nature these diseases are highly contagious, some amount of the health-aid could be diverted toward educating the general population on the early detection, causes, treatment/prevention measures, nutritional aspects, hygiene and sanitation, improving living conditions, etc., which could help lower the incidences of tuberculosis to a large extent. Basic levels of education play a key role in lowering the incidences of tuberculosis; hence both donors and recipient governments could direct a part of the funds toward meeting basic educational standards across the population at large. A major drawback of this analysis, however, lies in the fact that there are limited data on aid going specifically toward tuberculosis control. No meaningful regression analysis could be done with such limited data. Hence our closest approximation to conduct this study was to use the health-aid data. More efforts could be undertaken to collect more detailed data on specific communicable diseases. Future works may also focus on other infectious diseases like HIV/AIDS, malaria, etc. Also, better monitoring of the purpose for which aid is disbursed to recipient economies may help improve health outcomes.

Appendix A

Description of Data Used in Essay 1 (Chapter II)

Table A1: Countries in the Sample

Recipient	Time observations		Recipient	Time observations
Albania	2		Grenada	1
Algeria	1		Guatemala	5
Angola	5		Guinea	6
Argentina	1		Guinea-Bissau	5
Armenia	2		Guyana	2
Azerbaijan	1		Haiti	3
Bangladesh	5		Honduras	5
Belize	3		India	5
Benin	6		Indonesia	1
Bolivia	3		Iran	1
Botswana	1		Jamaica	3
Brazil	1		Jordan	2
Burkina Faso	5		Kazakhstan	1
Burundi	6		Kenya	1
Cambodia	2		Kiribati	2
Cameroon	6		Kyrgyz Republic	2
Cape Verde	4		Lebanon	2
Central African Republic	4		Lesotho	6
Chad	7		Macedonia	2
Chile	2		Madagascar	7
China	5		Malawi	6
Colombia	1		Malaysia	1
Comoros	2		Maldives	1
Congo, Dem. Rep.	6		Mali	7
Congo, Rep.	4		Mauritania	7
Cote d'Ivoire	4		Mauritius	3
Croatia	1		Mexico	2
Djibouti	5		Moldova	1
Dominican Republic	4		Mongolia	1
Ecuador	3		Morocco	3
Egypt	5		Mozambique	4
El Salvador	3		Namibia	2
Equatorial Guinea	1		Nepal	2
Eritrea	2		Nicaragua	4
Ethiopia	4		Niger	5
Fiji	2		Nigeria	3
Gabon	2		Oman	1
Gambia	4		Pakistan	1
Georgia	2		Papua New Guinea	4
Ghana	5		Paraguay	1

Table A1—Continued

Recipient	Time observations
Peru	2
Philippines	4
Rwanda	4
Samoa	1
Senegal	5
Seychelles	1
Solomon Islands	3
South Africa	2
Sri Lanka	2
St. Kitts and Nevis	1
St. Lucia	2
St. Vincent and the Grenadines	2
Sudan	4
Suriname	2
Swaziland	3
Syria	1
Tajikistan	1
Tanzania	4
Thailand	2
Togo	2
Trinidad and Tobago	2
Tunisia	1
Turkey	2
Uganda	5
Uzbekistan	1
Vanuatu	1
Venezuela	2
Vietnam	2
Zambia	6
Zimbabwe	4

Table A2: The List of CRS Purpose Codes

DESCRIPTION	Clarifications / Additional notes on coverage
HEALTH	
Health, general	
Health policy and administrative management	Health sector policy, planning and programs; aid to health ministries, public health administration; institution capacity building and advice; medical insurance programs; unspecified health activities.
Medical education/training	Medical education and training for tertiary level services.
Medical research	General medical research (excluding basic health research).
Medical services	Laboratories, specialized clinics and hospitals (including equipment and supplies); ambulances; dental services; mental health care; medical rehabilitation; control of non-infectious diseases; drug and substance abuse control [excluding narcotics traffic control (16063)].
Basic health	
Basic health care	Basic and primary health care programs; paramedical and nursing care programs; supply of drugs, medicines and vaccines related to basic health care.
Basic health infrastructure	District-level hospitals, clinics and dispensaries and related medical equipment; excluding specialized hospitals and clinics (12191).
Basic nutrition	Direct feeding programs (maternal feeding, breastfeeding and weaning foods, child feeding, school feeding; determination of micro-nutrient deficiencies; provision of vitamin A, iodine, iron etc.; monitoring of nutritional status; nutrition and food hygiene education; household food security.
Infectious disease control	Immunization; prevention and control of infectious and parasite diseases, except malaria , tuberculosis, HIV/AIDS and other STDs. It includes diarrhea diseases, vector-borne diseases (e.g. river blindness and guinea worm) etc.
Health education	Information, education and training of the population for improving health knowledge and practices; public health and awareness campaigns.
Health personnel development	Training of health staff for basic health care services.

- This table is reproduced from Source OECD, Development Assistance Committee.
- http://www.oecd.org/document

Table A3: List of Variables and Data Sources

Variable	Source
Infant mortality rate (IMR)	WDI, 2007
GDP per thousand (constant 2005 U.S. dollars)	WDI, 2007
Health-aid	OECD, CRS
Primary completion rate, total (%)	WDI, 2007
Physicians (per 1,000 people)	WDI, 2007
Population, total	WDI, 2007

Appendix B

Description of Data Used in Essay 2 (Chapter III)

Table B1: Countries in the Sample

Recipient	Time observations		Recipient	Time observations
Albania	2		India	4
Algeria	1		Indonesia	1
Angola	5		Iran	1
Armenia	2		Jamaica	1
Azerbaijan	1		Jordan	1
Bangladesh	4		Kazakhstan	1
Belize	1		Kenya	1
Benin	5		Kiribati	1
Bolivia	3		Kyrgyz Republic	2
Botswana	1		Lebanon	2
Burkina Faso	3		Lesotho	5
Burundi	5		Macedonia	2
Cambodia	2		Madagascar	7
Cameroon	5		Malawi	6
Cape Verde	3		Malaysia	1
Central African Republic	3		Maldives	1
Chad	7		Mali	7
Chile	1		Mauritania	7
China	5		Mauritius	2
Colombia	1		Mexico	1
Comoros	2		Moldova	1
Congo, Dem. Rep.	5		Mongolia	1
Congo, Rep.	2		Morocco	3
Cote d'Ivoire	3		Mozambique	4
Djibouti	5		Namibia	1
Dominican Republic	3		Nepal	2
Ecuador	2		Nicaragua	3
Egypt	4		Niger	5
El Salvador	1		Nigeria	3
Eritrea	2		Oman	1
Ethiopia	3		Pakistan	1
Fiji	1		Papua New Guinea	4
Gabon	1		Peru	2
Gambia	4		Philippines	3
Georgia	2		Rwanda	3
Ghana	4		Senegal	4
Grenada	1		Solomon Islands	1
Guatemala	4		South Africa	2
Guinea	5		Sri Lanka	1
Guinea-Bissau	3		St. Lucia	1
Guyana	1		St. Vincent and the Grenadines	2
Haiti	3		Sudan	2
Honduras	4		Suriname	2

Table B1—Continued

Recipient	Time observations
Swaziland	2
Syria	1
Tajikistan	1
Tanzania	3
Thailand	2
Togo	1
Tunisia	1
Turkey	2
Uganda	5
Uzbekistan	1
Venezuela	2
Vietnam	2
Zambia	6
Zimbabwe	3

Appendix C

Description of Data Used in Essay 3 (Chapter IV)

Table C1: Countries in the Sample

Recipient	Time observations		Recipient	Time observations
Albania	7		Guatemala	8
Algeria	6		Guinea	15
Angola	5		Guinea-Bissau	8
Argentina	4		Guyana	2
Armenia	6		Haiti	10
Azerbaijan	5		Honduras	10
Bangladesh	10		India	11
Barbados	1		Indonesia	6
Belize	4		Iran	5
Benin	14		Jamaica	6
Bolivia	9		Jordan	5
Botswana	5		Kazakhstan	6
Brazil	1		Kenya	2
Burkina Faso	12		Kiribati	2
Burundi	10		Korea, Rep.	1
Cambodia	8		Kyrgyz Republic	6
Cameroon	11		Lebanon	7
Cape Verde	10		Lesotho	10
Central African Rep.	9		Macedonia	5
Chad	11		Madagascar	14
Chile	1		Malawi	15
China	12		Malaysia	3
Colombia	3		Maldives	4
Comoros	8		Mali	13
Congo, Dem. Rep.	12		Marshall Islands	1
Congo, Rep.	5		Mauritania	9
Costa Rica	3		Mauritius	3
Cote d'Ivoire	11		Mexico	3
Croatia	1		Moldova	5
Djibouti	8		Mongolia	6
Dominica	1		Morocco	7
Dominican Rep.	8		Mozambique	14
Ecuador	4		Namibia	7
Egypt	8		Nepal	8
El Salvador	7		Nicaragua	9
Equatorial Guinea	6		Niger	11
Eritrea	7		Nigeria	3
Ethiopia	9		Oman	4
Fiji	3		Pakistan	1
Gabon	2		Panama	1
Gambia	8		Papua New Guinea	6
Georgia	5		Paraguay	1
Ghana	11		Peru	5

Table C1—Continued

Recipient	Time observations
Philippines	8
Rwanda	7
Samoa	1
Senegal	9
Solomon Islands	3
South Africa	8
Sri Lanka	1
St. Lucia	2
Sudan	7
Suriname	5
Swaziland	7
Syria	5
Tajikistan	5
Tanzania	9
Thailand	5
Togo	7
Tonga	1
Tunisia	6
Turkey	6
Uganda	13
Uzbekistan	5
Vanuatu	1
Venezuela	4
Vietnam	7
Zambia	12
Zimbabwe	10

Table C2: List of Variables and Data Sources

Variable	Source
Incidence of tuberculosis (per 100000 people)	WDI, 2007
GDP per capita	WDI, 2007
Health-aid	OECD, CRS
Primary completion rate, total (%)	WDI, 2007
Physicians (per 1,000 people)	WDI, 2007
Population density (per square km.)	WDI, 2007
GINI index	WDI, 2007
Health expenditure per capita	WDI, 2007

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