UNITED NATIONS UNIVERSITY

UNU-MERIT

Working Paper Series

#2012-057

The impact of development aid on education and health: Survey and new evidence from dynamic models

Thomas Ziesemer

Maastricht Economic and social Research institute on Innovation and Technology (UNU-MERIT)
email: info@merit.unu.edu | website: http://www.merit.unu.edu

Maastricht Graduate School of Governance (MGSoG)
email: info-governance@maastrichtuniversity.nl | website: http://mgsog.merit.unu.edu

Keizer Karelplein 19, 6211 TC Maastricht, The Netherlands
Tel: (31) (43) 388 4400, Fax: (31) (43) 388 4499

UNU-MERIT Working Papers

ISSN 1871-9872

Maastricht Economic and social Research Institute on Innovation and Technology, UNU-MERIT

Maastricht Graduate School of Governance MGSoG

UNU-MERIT Working Papers intend to disseminate preliminary results of research carried out at UNU-MERIT and MGSoG to stimulate discussion on the issues raised.

The Impact of Development Aid on Education and Health: Survey and New Evidence from Dynamic Models – Version 2

Thomas H.W. Ziesemer, Maastricht University, Department of Economics, and UNU-MERIT, P.O. Box 616, NL 6200 MD Maastricht, The Netherlands.
E-mail: T.Ziesemer@maastrichtuniversity.nl.

Abstract. We investigate the impact of aggregate aid, earmarked aid, committed or disbursed, on social indicators in health and education. A literature review shows that for earmarked aid use of commitment data mostly leads to insignificant results; use of disbursement data mostly leads to significantly favourable results; panel data models including lagged dependent variables lead to significantly favourable results for at least one form of aid unless only commitment data are used. In our own analysis of effects of aggregate aid per capita on life expectancy and literacy in low income countries we find from detailed analysis of lag structures that the data for literacy and life expectancy in dynamic panel data models should be taken in the form of growth rates. Growth rates of aid per capita are shown to have significantly favourable effects on the growth rates of life expectancy. Growth rates or levels of aid per capita may reduce growth rates of illiteracy in system GMM estimates. This version of the paper deals quantitatively with bias issues and optimal number of instruments raised by second generation Monte Carlo studies for system GMM.
JEL codes: F35, I15, I25. Keywords: foreign aid, education, health, low-income countries.

1. Introduction

The debate on the effectiveness of aid traditionally focussed on the link between aid and growth and from there has moved on to institutional aspects of donor and receiving countries. This paper's empirical analysis is more concerned with the outcomes in the social and poverty dimensions about which little was known until recently (White 2001) but has made some progress during recent years. More specifically, the focus will be on education and health, two crucial human capital aspects and development goals in their own right. The United Nations Millennium Declaration heeded this fact by devoting goal 2 to universal education and goals 4, 5 and 6 to health related issues. Not only is human capital augmentation a necessary pre-requisite to growth and therefore of interest even when the aid-growth relation is the prime issue, but also is it vital to the poor who mostly have to rely on the sale of their labour to generate income.

Yet, education and health are rather abstract concepts so that in order to be used in empirical work, some precise measures have to be chosen. Among the available empirical indicators, the illiteracy rate is used to proxy for education while the life expectancy at birth is taken as representative for the health condition of the population. These indicators have the following advantages.

In a developmental context, education during the last decennia often meant primary schooling because the ability to read and write is crucial for the poor to escape poverty. Therefore, the illiteracy rate is an important and poverty relevant indicator for education.

The health condition of a population can be expressed by several factors such as child mortality, incidence of AIDS and other diseases or number of doctors or hospital beds per 1000 persons. All of this information affects life expectancy at birth, which is an aggregate measure for health.

In this paper we provide a survey explaining why results in the literature are so controversial in section 2 and we carry out a panel data analysis of the impact of development aid per capita of the receiving country on illiteracy and life expectancy. The data are described in section 3; the econometric methodology in section 4; the empirical results in section 5; section 6 concludes.

TABLE 1 OVER HERE

2. Literature survey[1]

In this section we briefly summarize the results of previous literature. More detailed information is available in Table 1. At the end of this section we use this information for a more structured interpretation of the literature.

Boone (1996) finds a negative effect of the level of the aid/GNP ratio on the growth rates of infant mortality and primary schooling and a positive effect on the change of life expectancy. However, all effects are insignificant, possibly because a large set of control variables is employed, which may not only pick up all indirect effects but also cause collinearity in particular with GDP variables. Burnside and Dollar (1998, 2000) show that overall aid interacted with a policy index reduces infant mortality unless the policy index is zero. Gomanee et al. (2005a) find a negative effect of aid on mortality with stronger and more significant effects for poorer countries in a quantile regression. Gomanee et al. (2005b) confirm these results using fixed effects estimation and extend them to middle-income countries.[2] Gross (2003) finds favourable effects of aid per capita on illiteracy and life expectancy. He uses levels of all variables. For literacy this leads to a coefficient of the lagged dependent variable larger than unity, indicating an unstable difference equation. When a time trend is used instead the coefficient is below unity but a time trend implies that the variables grow beyond all more or less natural limits such as zero or

[1] We order the papers roughly according to appearance, which follows partly from the years of publication and from mutual referencing, leaving some room for imperfections of course. A list of abbreviations can be found at the end of the paper.

[2] The two papers also differ in that the 2005a paper finds – similar to Mosley et al. (2004) - significant effects of an index of public expenditure on education, health, and sanitation on the HDI index and infant mortality for some quintiles of the dependent variables.

hundred for literacy or slightly higher values for life expectancy. This suggests having unit roots and requires a more careful look at the lag structure of lagged dependent variables, one of the contributions of this paper. Bhaumik (2005) finds for African countries that World Bank assistance has a significantly negative effect on infant mortality and significantly positive ones for completing primary education, with all variables in first differences by assumption. However, when looking at mortality prior to the fifth birthday and youth literacy a 15% significance level applies; for progressing to fifth grade results become insignificant also at 15% level and have unexpected signs. Michaelowa (2004) finds a positive effect of education aid (also when taken per unit of GDP or per capita) on primary enrolments. Masud and Yontcheva (2005) find that bilateral aid and NGO aid, both in per capita terms, have no impact on illiteracy, but NGO aid has an impact on infant mortality as long as GDP per capita is not in the regression – the latter may cause collinearity problem as NGO aid goes to countries with more mortality which are poorer countries. There is also no indirect effect of these forms of aid via government expenditure on health or education. Fielding et al. (2006) develop a simultaneous equation model and find favourable direct and equilibrium effects of overall aid per capita on infant mortality and schooling; the effect on schooling is insignificant though and its equilibrium effect small. Wolf (2007) investigates the impact of aid on sanitation, water, infant and under-5 mortality, primary completion rates, and youth literacy. Four aid variables are used simultaneously: aid/GNI and its coefficient of variation, aid earmarked for water and its interaction with control of corruption. Aid/GNI has unfavourable or insignificant effects. The volatility indicator has favourable effects on water, sanitation and mortality. Earmarked aid has favourable effects only in health and education but not in water and sanitation. Interaction with control on corruption has a significantly favourable effect only for water if a federalism indicator is included, but not without. Williamson (2008) finds that aid per capita earmarked for the health sector has no impact on five health indicators in a fixed effects estimate using five and three year averages of data for 208 countries. In contrast, Mishra and Newhouse (2009) using lagged dependent variables find a reduction of infant mortality through health aid per capita or per unit of GDP, but no such effect of overall aid. Dreher et al. (2008) find a positive effect of per capita aid for education on primary school enrolment, but not for total disbursed aid. Gyimah-Brempong and Asiedu (2008) find favourable effects of earmarked aid (per capita and per unit of GDP) on primary completion rates[3] and infant

[3] The use of system GMM in spite of the absence of a lagged dependent variable together with insignificance in the fixed effects estimate suggests that the effect stems from the first difference equation in the system

mortality. Chauvet et al. (2008) find that health aid per capita is reducing infant and child mortality if health aid per capita interacted with per capita income is added as a control variable. D'Aiglepierre and Wagner (2010) find a significantly positive effect of aid per capita earmarked for education on enrolments and also a favourable impact for the achievement variables gender parity in enrolment, the primary completion rate and the repetition rate. Wilson (2011) finds no effect of committed development assistance for health on infant mortality. Ziesemer (2011a) finds a positive direct impact of the aggregate aid/GDP ratio on literacy together with a positive impact of public expenditure on education[4] and a positive indirect effect of aid via public expenditure on education, both as a share of GDP. Arndt et al. (2011) find a positive effect on aggregate aid per capita on life expectancy in a cross-section regression only when using Inverse Probability Weighted Least Squares (IPWLS), but not when using OLS or LIML. Gillanders (2011) reports positive impulse responses from shocks of aid per capita on the growth rate of life expectancy in a PVAR (panel vector autoregressive) model; they are stronger if countries are democratic and have good institutions. Burguet and Soto (2012) find that infectious-disease aid (IDA) per capita reduces under-5 mortality mainly through malaria and STD/HIV control, but also due to the other IDA components. Feeny and Quattara (2013) find significantly positive effects of health aid as percent of GDP on rates of immunization for measles and DPT (Diphtheria-Pertussis-Tetanus). Mukherjee and Kizhakethalckal (2013) show that health aid per capita reduces infant mortality (in a highly nonlinear way) if primary school completion rates are above 38%, which is outside the lowest quintile. This happens mostly through nutritional aid and perhaps prenatal care. A more detailed look at the data and estimation methods shown in Table 1 suggests the following conclusions.

Gross (2003), Michaelowa (2004), Dreher et al. (2008), Mishra and Newhouse (2009), Gyimah-Brempong and Asiedu (2008) (for mortality but not for the primary completion rate)[5], Wilson (2011), Ziesemer (2011a) and Gillanders (2011) use lagged dependent variables and dynamic panel data methods (see Table 1, column 7).[6] Close to using

---

GMM estimation.

[4] To get the significance a polynomial distributed lag is used because money flows from one year alone are unlikely to have effects in a world where education financing almost never leads or pushes the process but rather does or does not follow the enrolments some time later.

[5] Effects for overall aid are not documented but reported verbally to be insignificant.

[6] Burnside and Dollar (1998) do not use exactly a lagged dependent variable but besides their four-year averages of data they use also the initial value of infant mortality in these periods. Masud and Yontcheva (2005) use lagged dependent variables only in their regression of government expenditure on education and health expenditure on bilateral and NGO aid. They find no effect of current aid. It remains unclear why they do not see persistence in the regressions for mortality and illiteracy. Mishra and Newhouse (2009) use lagged dependent variables and show that doubling health aid significantly increases health expenditure by

lagged dependent variables is Boone (1996) who uses initial values in OLS regressions (no fixed effects) with ten-year-averaged data, which make them essentially cross section regressions though (see also footnote 4 in Gomanee et al. 2005a). In one regression he uses five-year averages, but then an initial value is not the same as a lagged dependent variable. Similarly, Burnside and Dollar (1998) use initial values in four–year averages. Interestingly, with the exception of Wilson (2011) using commitment data,[7] all of the papers using lagged dependent variables and the adequate dynamic panel data methods find positive effects of some form of aid on the social indicators considered, whereas the evidence from the other papers is much more mixed. Although several authors find that regressions with lagged dependent variables - in particular when using GMM methods[8] - tend to find a low number of significant regressors, aid turns out to be significant.

Moreover, a look at Table 1, column 4, shows that for earmarked aid use of commitment data mostly leads to insignificant results; use of disbursement data mostly leads to significantly favourable results. We think it is too pessimistic to say that only enrolments have been improved through aid (Riddel 2012). Our survey and the contribution below show that there are also effects on primary completion rates and literacy.

The channels along which aid affects social and poverty variables according to the literature discussed are the following. Aid affects the HDI, social and poverty indicators (i) directly and (ii) indirectly via growth (Collier and Dollar 2002), and (iii) via public expenditure (Mosley et al. 2004; Gomanee et al. 2005a; Mishra and Newhouse 2009), (iv) through interactions among several social indicators such as female education decreasing infant mortality and thereby life expectancy (Fielding et al. 2006; Feeny and Quattara (2013); Mukherjee and Kizhakethalckal (2013)); and (vi) via a combination of some of these channels affecting infant mortality, primary enrolment or literacy either via

---

7% but the effect of overall aid is insignificant. Ziesemer (2011) uses dependent variables lagged one year in a regression for public expenditure on education and finds an effect of aid/GDP lagged five years. Governments may react differently in the short and the medium run.

[7] Wilson's paper has some strange properties. First, the literature discussion does not even mention the papers by Gyimah-Brempong and Asiedu (2008) and Mishra and Newhouse (2009), which both find a positive effect of aid on infant mortality. Second, as OLS overestimates the coefficient of the lagged dependent variable and fixed effects least squares underestimates it the GMM estimators of Arellano, Bond, Bover, Blundell should come up with coefficients between those from OLS and FELS, but in Wilson's paper the AB-GMM estimator leads to a coefficient higher than that of OLS which points to a false handling of it, which might have an effect on the significance of the aid variable. Third, committed aid excludes effects of aid from budget aid and includes parts of non-disbursement and one needs more sophistication in finding the disbursement lag for example through application of polynomially distributed lags.

[8] See Michaelowa (2004) and Dreher et al. (2008). Lagged dependent variables are always highly significant not only in the macroeconomic literature but also in that discussed in this paper. Omission of lagged dependent variables therefore may cause an omitted variable bias. Another important aspect is that aid is likely to be endogenous if it is earmarked to a purpose captured by a dependent variable (see for example Michaelowa (2004); Dreher et al. (2008), Mishra and Newhouse (2009), Burguet and Soto (2012)).

multiple equation approaches (Ziesemer 2011a) or by not limiting the specification to certain channels as most papers do.[9]

In order to avoid the complications of large systems of equations, we do not distinguish the different channels but rather estimate the total effect of aid with and without control variables, which mostly turn out to be insignificant though once lagged dependent variables are employed.

3. The data

We will not use earmarked aid for several reasons: first, its favourable effects have been shown repeatedly now, provided it is also disbursed; second, budget aid may also be used to target the social indicators without being earmarked by donors (Wolf 2007; d'Aiglepierre and Wagner 2010) and, third, because earmarked aid may underestimate the indirect effects after the first round of spending; fourth, there is an increasing share of budget aid in total aid (Wolf 2007).

We work with three data sets. All data have been taken from the World Bank's "World Development Indicators". All samples cover 65 low-income countries as defined by the World Bank[10] in 2003. In the first data set (from Gross 2003) observations are available for the years 1960 – 2001 and are arranged in 5-year averages of eight periods from 1961-1965 to 1996-2000. This has the advantage of smoothing the data, filling single years of non-availability and also accounts for the fact that effects often do not materialize immediately but with an unknown lag. Generally speaking, the data coverage is weak especially for the first decade in the sample but improves for the later periods to almost full coverage in the 1990s. The investigation with five-year data makes the time dimension short and puts emphasis on the cross-country dimension. Second, we also investigate these data using the yearly data until 2001, thereby shifting emphasis more to its end where the coverage is better; as the time dimension becomes larger emphasis also shifts away from the cross-section to the time-series dimension and gets more in line with policy advice hoping for intertemporal effects. The third data set wants to employ the recent good coverage with yearly data from 1960-2010 from World Development Indicators 2012 and therefore puts even more emphasis on the time dimension. However, the coverage for this period is weak for illiteracy.

[9] Verschoor and Kalwij (2006) also discuss the possibility that aid changes the income elasticity of poverty.
[10] Appendix 1 provides a list of the countries used in the analysis. Using larger sets of countries is likely to suffer from coefficient heterogeneity as shown by the quintile regression of Gomanee et al. (2005a) this can also lead to insignificant coefficients.

In order to examine the relationship between aid and education and health, respectively, the following dependent variables were used as proxy variables (see Table A.1 for details):

- *Ill*: a percentage measure of the total adult population (15 and above), which is not literate. The illiteracy rate will serve in this analysis as an indicator of education. Due to many revisions there are fewer yearly observations available in the recent samples. For countries where old and new data had overlap and were numerically identical we did add the old to the new data. Still the number of observations is lower for recent periods because some countries with many observations in the early period have none in the later period. The data in Table A.1 show that there is a slight fall in illiteracy over time when comparing panel (b) with (c).
- *Life*: total population's average life expectancy at birth in years. This variable is very well documented and therefore commonly used in empirical applications. The data span all 65 countries with only a few observations missing. There is only a slight increase in life expectancy in Table A.1 from panel (b) to (c).

These development indicators are thought to represent the wider poverty concept and were related to the following independent variables[11]:

- *Aid*: aid per head in constant 1995 (2009) US Dollar as the original current US Dollar series were deflated with the OECD's deflators for resource flows from DAC members and indexed for 1995 (2009). This is the variable of prime interest in this analysis. Data coverage is good. It is expected that aid will have a negative coefficient in the estimation of the illiteracy rate and a positive one in the regression of life expectancy. A comparison of panels (b) and (c) in Table A.1 shows that aid per capita has grown strongly in the recent years.
- *gdp*: GDP per capita in constant 1995 (2000) US Dollar. It is assumed that GDP has a significant impact on the dependent variables analogous to that of aid.
- *pee*: public expenditure on education expressed as a percentage of GDP. The variable on education spending will only be used in estimating illiteracy and is anticipated to have a negative effect. Data availability is reasonably good. Again, due to data revisions yearly observations are less in the more recent sample.
- *Health*: total health expenditure expressed as a percentage of GDP. In this analysis, data on health spending are the scarcest. In fact, they are just available

[11] As military expenditure had no effect in all our efforts we do not include them in the data.

for the periods after 1985, which will markedly reduce the number of observations that can be used for a regression once health expenditure is included. In the more recent data set they start in 1990 only. Naturally, it is expected that health spending has a positive effect on life expectancy.

- *Rural*: proportion of the population living in rural areas. This variable is aimed at capturing some of the country-specific characteristics. Assuming that a high proportion of rural population has detrimental effects on literacy and life expectancy, this variable should be important. Furthermore, data coverage is almost perfect. Surprisingly though, the variable is not falling on average as they have roughly the same mean in the three data sets of Table A.1.
- Among the low-income countries, 38 are in Sub-Saharan Africa. But a dummy for Sub-Saharan Africa plays ultimately no role in our results.
- *Nineties*: dummy variable; 1 for the more recent periods since 1991and zero otherwise. The nineties dummy was introduced in order to be interacted with aid. It was included, because several authors and aid agencies claimed that the manner of giving aid by donors had become more effective, in part due to the implementation of findings of the effectiveness debate[12]. Constructed that way, it should capture any improvements of aid policies in that decade, e.g. through policy conditionality or tighter selectivity.

As five-year intervals take out a lot of variation and reduce the time dimension and also have other disadvantages[13], we also use the yearly data first until 2001 and then until 2010.

4. Methodology

Without lagged dependent variables no distinction between short term and long term effects can be made[14] and the dynamics in the panel data is not used. If one wants to put emphasis on the dynamics, it is important that policy takes time to have effects and five-year lags seem more plausible then ten-year lags (Mishra and Newhouse 2009). We emphasize the role of fixed effects, lagged dependent variables, and first-differences specifications for all variables. We find first differences as the relevant way of using the

[12] See e.g. Hudson and Mosley (2001) who emphasize the shift to technical and program assistance in combination with policy conditionality as well as attempts to work around corrupt governments by channeling aid funds through NGOs or the private sector. Also the end of the cold war is mentioned as a reason. Indeed Mishra and Newhouse (2009) find such an effect.

[13] See Attanasio et al. (2000) for an extensive discussion.

[14] Note also that Smith and Fuentes (2010) reject the idea that cross-section regressions capture the long run.

data in system GMM by extensive consideration of several lagged dependent variables and the size of their coefficients. Similarly, Mishra and Newhouse (2009) find that their lagged dependent variable has a coefficient of unity and report in a footnote that estimation in first differences gives the same result. However, this may point to a fundamental misspecification and therefore deserves extensive analysis.[15] Moreover, when taking data in terms of differences fixed effects turn out not to be redundant whereas the use of the system GMM model assumes exactly that for level variables. We also avoid collinearity by not employing GDP variables on the right-hand side, implying that we do not treat direct and indirect effects via GDP per capita separately. [16,17] We could think of several other control variables than those of the previous section like number of physicians (used by Williamson 2008) but they are under suspicion of collinearity with (health) aid. Similarly, GDP per capita and freedom indicators are likely to be collinear, and so are (growth rates of) GDP per capita and aid (see Ziesemer 2011a for two-way causality), and the simultaneous use of four aid indicators in Wolf (2007). As collinearity has an impact on significance and sign this should be avoided. Given the panel structure of the data, pooled estimation techniques have to be used. The basis for the analysis of panel data in case of lagged dependent variables is given by the equation

$$y_{it} = \gamma y_{i,t-1} + \beta_0 + \beta_1 x_{it1} + \ldots + \beta_k x_{itk} + a_i + b_t + u_{it} \qquad (1)$$

Here i denotes cross sections, t denotes periods and $1, \ldots, k$ denotes the explanatory variables other than the lagged dependent variable. The regressors x_{itk} cover the effects, which are variable over time, whereas the a_i term represents the unobserved or fixed effects for cross-section units and b_t those of periods of time. The country-specific effects may be correlated with the regressors. For all our regressions we have tested for the redundancy of fixed effects, which was never found though. A Hausman test also indicates in all cases that random effects are not a superior conceptual alternative. Therefore we do not use the random effects model. [18] The fixed effects model though is

[15] It is not possible though to judge without detailed investigation. In this paper we find that differences of natural logs of illiteracy are the best specification. But Ziesemer (2011b) finds two significant lags but the specification with slightly different coefficients in levels is preferred. Ziesemer (2011a) finds no relevance of differences. These results seemingly depend on the control variables and the panel structure.

[16] Collier and Dollar (2002) take the opposite perspective. They assume that aid reduces poverty only through growth at a given distribution and better so under good policies. Mosley et al. (2004) show that aid has an impact on public expenditure policies and from there on poverty.

[17] Fielding et al. (2006) discuss many examples of two-way causality of GDP per capita with other variables related to health and education and collinearity has been a widely discussed topic in growth regressions. Ziesemer (2011a) separates direct and indirect effects through simultaneous equation modeling.

[18] See Baltagi (2008) and Greene (2008) on the following in addition to the other references given in the text.

also not without problems. The lagged dependent variable implies that a fixed effects estimate would underestimate its coefficient, γ, with an expected bias of order *1/T* if the lagged dependent variable is the only regressor, but smaller when there are more regressors (see Asteriou and Hall 2011, chap. 19). Using OLS, after dropping fixed effects by assumption when they are not redundant, would lead to overestimation of γ (see also Durlauf et al. 2005) and inconsistency. The true value, between those from fixed effects and OLS, could be obtained using the system GMM approach and it should be about *1/T* above that of the fixed effects estimator or less if more regressors are present. In its basic version it employs two equations: a level equation as in the within estimator and a first-differenced equation with coefficients restricted to be the same for both equations. The within estimator uses (lagged) first differences of the exogenous (endogenous or pre-determined) regressors and the first-difference equation uses (lagged) levels of the exogenous (endogenous or pre-determined) regressors as instruments. The first difference equation alone as suggested by Arellano and Bond (1991) used with many instruments for the sake of maximum efficiency has turned out to suffer from small sample bias and therefore only a few instruments should be used (Wooldridge 2002, 305). Monte Carlo studies by Blundell and Bond (1998) and Soto (2009) have shown that system GMM as just described is working well. As a comparison, we will present the underestimating fixed effects estimator and the overestimating ordinary pooled least squares estimation too. In another variant of the system GMM estimator the first-difference equation is replaced by orthogonal deviations, where the residual is diminished by the sum of future residuals, called Helmert transformation (see Arellano and Bover 1995). The advantage of this variant of the method is that the number of missing observations is not enhanced as it is when applying first differences to variables and instruments (see Roodman 2009a). As we have the problem of many missing observations when not averaging the data over five years but rather using yearly data we will use this method of orthogonal deviations. When choosing the number of instruments we follow the advice of Wooldridge (2002) to use a couple of lags rather than all back to t = 1. When using as many instruments as there are parameters to be estimated the J-statistic, minimized by the GMM methods, will be zero (see Greene 2008). When using more instruments than parameters to be estimated the GMM methods have over-identifying constraints. The J-statistic should increase from zero and have a chi-square distribution with degrees of freedom equal to the instrument rank minus the number of estimated parameters. If it increases too much the assumption of a chi-square distribution is violated either by invalid instruments or by mis-specification. It should therefore not increase too much (see Davidson and McKinnon 2004) and its p-value from the Hansen-Sargan test, *p(J)*, should not be too small (see Greene 2008). On the other hand, Roodman (2009b) points out that the increase of the J-statistic should also not be too low, because this could indicate that the additional instruments causing over-identification are ineffective in correcting the bias. In this case the p-value of the J-statistic from the Hansen-Sargan test should not be too high. For both of these reasons the p-value should not be too far out of the interval of 5% and 25% - leaving open so far what 'too far' exactly means. We will therefore report the values of the J-statistic and its p-values. We will start with a low number of instruments and test every additional instrument creating over-identification by a Sargan difference test. We add instruments when (i) we have a suspicion of low efficiency – the traditional reason for using many instruments -, (ii) when the Sargan test indicates that the J-statistic is too low, or (iii) if the regression coefficient of the lagged dependent variable is not larger than that of the fixed effects estimator. We stop adding instrument whenever the Sargan difference test is not passed with p-values again in or close to the interval of 5 and 25 percent or if the above three conditions are fulfilled. Okui (2009) has pointed out that there was so far no formal procedure to determine how many moment conditions should be used. The informal procedure just outlined above is based on our reading of Roodman (2009 a,b).[19] Okui (2009, Table 1) derives optimal numbers of instruments and we will compare our numbers to his.

Validity of instruments also requires absence of second-order serial correlation with coefficients larger than 0.2, where the Arellano-Bond test breaks down for smaller values (see Roodman 2009a). First-order serial correlation is always implied by orthogonal deviation and therefore no problem for the validity of instruments in this method. When it is strong though, one has to be careful about the basic serial correlation bias in connection with mis-specification. Adding more lagged dependent variables also when insignificant can be used as usual to reduce serial correlation to the amount inevitable under orthogonal deviations. We use time-fixed effects in order to limit the effects of cross-section dependence as suggested by Roodman (2009a).

Blundell and Bond (1998) and Soto (2009) use the assumption of equal unit variances for the fixed effects and the residuals in their Monte Carlo studies implying a variance ratio of unity. Okui (2009) has provided a Monte Carlo study for the orthogonal deviations version of system GMM for variance ratios of unity and ten. Bun and

[19] Andrews and Lu (2001) suggest a procedure starting with many instrument and reducing them until model selection criteria suggest an optimum. Okui (2009) arguess out that their method serves for the distinction between correct and incorrect instruments.

Windmeijer (2010) have shown that for a ratio of four there is an upward bias of the system GMM estimator of about 9% if $T = 6$ and of about 7% if $T = 15$. Okui (2009) and (Bun and Windmeijer (2010) do not add other regressors and therefore the biases they find provide upper limits. Bazzi and Clemens (2010) deal with the endogeneity of one endogenous regressor in addition to the lagged dependent variable. They show that in addition to the Bun/Windmeijer results, (i) the regression coefficient of the regressor and its own lag used as an instrument should be high and (ii) the correlation coefficient between the residual of the latter equation and the equation of interest should not be large. Hayakawa and Pesaran (2012) have added one exogenous regressor in addition to the lagged dependent variable. They carry out the Monte Carlo study for variance ratios of unity and five. Although only Okui (2009) deals with the orthogonal deviation method we use here, we will report the variance ratio, the correlation coefficient and the regression coefficient emphasized by these considerations. All papers cited above emphasize that the bias found by different methods depends on the number of cross-sections and periods, the variance ratio, and the size of the coefficient of the lagged dependent variable and the other endogenous regressors. After all, Bazzi and Clemens (2010) suggest improving the use of system GMM and not to abandon it.[20]

Before applying the rigorous method though one has to find the adequate specification or data generating process, DGP, or true model, which is assumed to be known in the econometric textbooks and known in Monte Carlo studies. Experimentation with logs, lags, squares and differences of the fixed effects estimator leads us to the result that data should be taken in logs at least for the life expectancy variable, but less clearly so for illiteracy. Moreover, data should mostly be taken in terms of first differences when used in the approach of equation (1). This should not be mixed up with differentiating equation (1), because that would imply a first difference (moving average process) of the residual. The tables with results will indicate which specification was most successful in regard to logs, lags, squares and differences. The versions of equations (2) and (3) below are only indicative.

The underlying question is whether aid is effective in combating illiteracy and improving life expectancy. Therefore, the equations to be estimated are in the first instance:

$$d(\log(ill_{it})) = \varphi d(\log(ill_{i,t-x})) + \alpha_0 + \alpha_1 d(\log(aid))_{it} + \alpha_2 nineties * \log(aid)_{it} + a_i + b_t + u_{it} + controls \quad (2)$$

[20] Hayakawa and Pesaran (2012) suggest an alternative method for the case of one additional exogenous regressor. Discussion of bias correction methods is beyond the scope of this paper.

and

$$d(\log(life_{it})) = \delta d(\log((life_{i,t-1})) + \xi_0 + \xi_1 d((\log(aid))_{it}$$
$$+ \xi_2 nineties * d(\log(aid))_{it} + c_i + f_t + u_{it} + controls \qquad (3)$$

In order to make a judgment on aid effectiveness in terms of the dependent variables, the coefficients on log(aid) and on the interaction term nineties*log(aid) are of primary interest, either in levels or in first differences. Including or dropping time dummies will be indicated in the notes to the tables. All the other explanatory variables described above were added too when trying to find a good specification. Lagged and squared terms with and without natural logarithms were included where appropriate and statistically significant. The interpretation of having mostly first differences in the data is that life expectancy and illiteracy change anyway, but aid or its changes can speed up or slow down this process.

Finally, in order to avoid results being driven by outliers (Chatelain and Ralf 2012) we run bi-variate nearest-neighbour-fit or kernel-fit regressions of the aid variables on the dependent variables both as defined in Tables 2-4. These regressions can have changing slopes which may be different in the region of outliers then they are where the most observations are. In such a case, if our regressions would have the slope of an outliers region rather than that of the region with most of the data we would have found a case of an outlier driven result.

5. Estimation results

In order to find a good specification we first run fixed effects estimates with both 5-year averaged data and yearly data. We first report these preliminary fixed effect results and then those for system GMM and the corresponding OLS and fixed effects estimates in order to compare the coefficients for the lagged dependent variable.

Preliminary fixed effects results

The results are collected in the Table A.2 of the Appendix. Regressions are in log-differences for life expectancy, implying a five-year growth rate, and in five-year differences for illiteracy. We first discuss those going until 2000/2001 in equations (1), (2), (4) and (5) and later those going until 2009/10 in equations (3) and (6).

Lagged dependent variables are always significant. Illiteracy has a negative change throughout, which is reinforced by the coefficient of the lagged dependent variable. For life expectancy there are countries with positive and with negative growth rates. For positive growth rates the negative coefficient of the lagged dependent variable implies that it is reduced; for negative variables it is increased.

Growth rates of development aid per capita have favourable signs and are significant in one or other form suggesting that non-linearities play a role. The dummy for the 1990s is significant only for the illiteracy equations, supporting the suggestion that aid policies have improved compared to earlier periods.

As Chauvet et al. (2008), we find that many control variables are not significant. In the equations for life expectancy we find that health expenditure per unit of GDP is significant. The first difference has a positive sign, but the first difference of squares has a negative sign. For 5-year average data there are only three data points for 1990-2000 we have only two in first differences and the result is mainly caused by the cross-section dimension. The values of the 5-year differences in the health variable are mostly between -4 and 4 and those for the squares between -40 and 40. The estimated coefficients differ by a factor ten as well indicating a positive but diminishing effect of health expenditures as a share of GDP on life expectancy. Elementary simulation work (not shown) suggests that the total effect is positive but decreasing over time.[21] A higher percentage of rural population leads to a higher growth of life expectancy and a quicker fall in illiteracy. When adding time dummies to equation (2) (not shown) 'rural' becomes insignificant, but other results in equations (2) and (5) change only marginally. Time dummies do not change sign or significance for equation (5). GDP per capita growth speeds up the growth of life expectancy when using yearly data but has no impact on the change of illiteracy. Public expenditure on education as a share of GDP helps reduces the growth of illiteracy. Finally, changes in life expectancy reduce that in illiteracy, probably because a longer life time makes investment in education more profitable.

Using yearly data until 2010 in equations (3) and (6) of Table A.2 by and large confirms the earlier results. There are some important exceptions though. In equation (3) the health variable gets a negative sign and the rural indicator also changes sign, casting some doubts on the robustness of these variables. In equation (6) other variants of the education variables are significant. Simplified simulations with lags ignored show that

[21] We regress the health variable on a constant and a time trend (higher exponents are insignificant), which yields a coefficient of 0.02 for the trend. First differences are then 0.02; for the difference of the squared variables though differences are 0.7 in the beginning but first increasing, leading to a positive but later decreasing result for about 70 years when it becomes zero and negative.

there is a non-linearity such that public expenditure on education has a positive effect on the change of illiteracy between values of 1.5 and 3.5 percent. This may happen to occur if the money is shifted into secondary schooling and teachers are competed away from primary schooling. However, we will show below that the variable does not appear when system GMM is used.

TABLE 2 OVER HERE

System GMM results for life expectancy 1960-2000

Table 2 shows the results for 5-year average data in columns (1) - (3) and for yearly data in columns (4)-(6). The results for 5-year average data are very similar to those of the preliminary results for lagged dependent variables and growth of aid, but the growth rate of GDP per capita and the share of the rural population are insignificant now. But 5-yearly data are moderately interesting here because only one observation is left over in the time dimension, mainly because health data are available only since 1990 and taking differences and lags reduces the time dimension.

For yearly data[22] we find that also the health expenditure variable has dropped out when making the step to system GMM. Removing the bias in the coefficient of the lagged dependent variable has an impact on several variables that makes the coefficients insignificant. As health expenditure drops out under yearly data its impact when using the 5-year average data seems to stem from the cross-section emphasis.[23] The lagged dependent variable has a coefficient that is larger than the underestimating fixed effect estimate and smaller than the over-estimating OLS estimate. This also holds if one adds it up with the coefficient of the second lag.[24] As we use a five-year lag for the lagged dependent variable we use instruments that are lagged two periods more. As we use a further lag for the cubic term we have also applied the Hansen-Sargan difference test showing that we are close to the interval of 5-25% explained above. A Davidson/ MacKinnon test, which is similar to the Durbin-Wu-Hausman test, carried out in OLS

[22] Angola, Mongolia, and Mozambique have some years of negative aid observations, which we have set to 'not available' here, but not in the work for Table 4, where we have added a constant of unity to the variable under the log.

[23] This is an example for the more general result that the ratio of countries to periods, *N/T*, has an impact on the results (see Smith and Fuentes 2010 for the econometrics). It is therefore important to choose whether one wants to make a repeated cross-section analysis or to go as much as possible into the dynamics. We prefer the latter and therefore choose not only within estimators but also lagged dependent variables and yearly data.

[24] As life expectancy has a growth rate of less than 1%, adding up or not, the coefficients of the squared and cubic lags is irrelevant as they are too small because of their dimension.

does suggest endogeneity of the aid variable.[25] If one does carry it out in GMMSYS, because the instruments are lagged variables, it does not. As the latter is not standard we are cautious and use a lag as instrument. Without the lagged instrument for aid its coefficient in (5) would be 0.011 rather than 0.018. The major result is that a five-year growth rate of aid of one percent increases that of life expectancy by 0.011% or 0.018%. Testing for the independence of the 5-year lagged residuals from those belonging to the 7-year lagged instruments via second-order serial correlation with 5-year lags yields a negative coefficient. As the Arellano-Bond tests are valid only coefficients above 0.2 the Hansen test is relevant (Roodman 2009a) and indicates validity of instruments and specification. The orthogonal deviation variant of system GMM always has first-order serial correlation and therefore we do not have to test for that.[26]

TABLE 3 OVER HERE

System GMM results for illiteracy 1960-2001

These results are shown in Table 3. For illiteracy there is a change from non-log to log differences, which is the more successful specification when compared to the preliminary results of Table A.2. Most regressors become insignificant: life expectancy, rural population share and public expenditure on education. Aid remains significant in terms of levels interacted with the dummy for the nineties in equation (2) using 5-year average data. In the yearly data the lagged and squared 5-year growth rate of aid has a similar effect. Aid has to be turned into enrolments, avoiding drop out and then literacy is measured in the population above age 15, which explains that one has at least a five year lag. Coefficients for the lagged dependent variables in the system GMM are again between those of OLS and fixed effects estimates. A five-year growth rate of aid of one percent reduces that of illiteracy by 0.4% in equation (5). Additional lags have been added here only as serial correlation correction, a purpose they may serve although they are insignificant (Greene 2008). As they are insignificant we prefer not to add them up with the coefficients of the first lag. As we do not use more than one instrument per regressor we have no over-identification and the Hansen J-statistic is zero in equations (2) and (5). A panel version of Durbin-Wu-Hausman test by Davidson and McKinnon (2004) using OLS shows no endogeneity for the aid variable in equation (2). As instruments are lagged dependent though, we also carry out the test in terms of fixed effects and GMMSYS. These two versions do indicate endogeneity and therefore we used the lagged

[25] The residuals from a first-stage regression are added to the equation. If they are significant, instruments should be used. See Davidson and McKinnon (2004) and Masud and Yontcheva (2005).
[26] The econometrics of the last five lines can be learned from (Roodman 2009a).

regressor as instrument. If the regressor is used as instrument instead of lagged aid the coefficients in equation (2) are 0.916, -0.0014, which is only slightly different. For panel corrected standard errors we use the period-SUR version here as orthogonal deviations always imply first-order serial correlation (Roodman 2009a) but it should not bias the standard errors.[27]

Summing up, the firm conclusion can be drawn that aid per capita has significant and non-trivial effects on life expectancy and illiteracy but all variables have to be taken in growth rates, except for the case of five-year averages in illiteracy where aid contributes in terms of levels to the growth rate of illiteracy. In order to reach the maximum decline in the illiteracy rate, aid per capita should keep growing. It remains an open issue though to investigate the channels how aid growth contributes to growth of life expectancy and illiteracy. The analyses of channels indicated in the literature review mostly do not use dynamic econometric methods. But our analysis does not exclude any of these channels as implausible. To the contrary, the variables that drop out from the preliminary fixed effects estimates in Table A.2, in particular the growth variable for life expectancy and public expenditure on education for the illiteracy regression may drop out exactly because they are the channel.

TABLE 4 OVER HERE

System GMM results for life expectancy and illiteracy 1960-2010

In Table 4 there are two lagged dependent variables and the sum of their coefficients obeys the rule that they are higher in equations (2) and (5) respectively than for the corresponding fixed effects estimates (1) and (4) and lower than for the OLS estimates (3) and (6).

The five-year growth rate of aid per capita, instrumented with its own one period lag, increases life expectancy in equations (1) and (2).[28] As we have $T = 36$ the expected bias is less than $1/36$ and therefore the fixed effect estimate is usually also held to be acceptable.[29]

---

[27] Second-order serial correlation of ten or fifteen period lagged residuals on the current or 5-year lagged residuals cannot be tested because there are too little data.

[28] In order to avoid logs of negative numbers we have enhances the aid value by 1.

[29] In equation (2) we have second-order serial correlation of *-0.08*; the Arellano-Bond test is valid only for *0.2* and larger (Roodman 2009a). In equation (5) we have second-order serial correlation invalidating the instruments for the lagged dependent variables. However, with $T = 27$ the fixed effects estimate has an expected bias in the coefficients of the lagged dependent variables of less than $1/27$. The fixed effects estimate (4), which is not relying on instruments and absence of second-order serial correlation and consistent for T towards infinity, confirms the result.

For literacy the log-level of aid matters. Instead of the squared value shown in equations (4) and (5) we could also use the linear variable or its cubic version without change in sign or significance, or all the three of them, leading to the lowest standard error of estimation, but also to collinearity. The effect of the quadratic version is shown in Figure 1. Using also the quadratic and the cubic term leads to the same graph with invisibly small differences. The log-level of aid reduces the growth rate of illiteracy again with a long lag suggesting that the education system is the channel, where effects on pupils with young age are only measured in the literacy data when they are fifteen years old.

FIGURE 1

Bias considerations according to second generation Monte Carlo studies

There are two types of biases under consideration. First, the estimate of the lagged dependent variable may be biased if the ratio of the variances for fixed effects and the residuals are above unity; below unity the bias is in the order of magnitude of -1% shown by Bun and Windmeijer and not considered by the other papers later. Table 5 shows that we find variance ratios larger than unity only in two of six cases. In column 1 we have a variance ratio above eight for $T=1$ and no bias no information is available for such a low T from Monte Carlo studies. From the criterion that the fixed effects estimator is too low by $1/T$ we can only infer that our system GMM estimator is between that of OLS and the within estimator as it should.[30] In column 4 we have a variance ratio of 5.2. Tables of Okui (2009)[31] suggest a bias of about -0.04 whereas the $1/T$ criterion would suggest we overestimate the coefficient of the lagged dependent variable. Nothing in our conclusions above would suffer from a bias of four percent.

Second, the coefficient of other regressors than the lagged dependent variable, in our case the aid variable, may be biased if the correlation coefficient of the residuals of the regressions with that from regressing the aid variable on its instrument is large and the regression coefficient is low (Bazzi and Clemens 2010). In three of our cases this is irrelevant because there was no endogeneity according to the Durbin-Wu-Hausman test. In the other cases of endogenous aid variables we find only a very small correlation of the residuals and a fairly high coefficient in the autoregressive aid regressions indicating persistence rather than weak instruments. The biases are slightly negative which means that the effect of aid on life expectancy is even stronger than we have shown and the

[30] If we really should expect a bias of $1/T = 1$ then our estimator is too low. However, with a squared term involved we get another uncertainty because these cases have not been treated in econometric analyses.

[31] Hayakawa and Pesaran (2012) use too many instruments to get a bias value in this case.

effect of aid on illiteracy is negative meaning that aid may help slightly less here than estimated in Table 3; but in Table 4 using all observations the result that aid is reducing illiteracy is unaffected. Overall, we find biases that do not impair our conclusions simply because they do not depend on having coefficients five percent larger or smaller than the estimate. However, we would like to caution that only a very few cases have been covered in the Monte Carlo studies. In particular high coefficients of lagged dependent variables cause worries, but it is unclear how this works out in the relevant cases of most of the applied papers: the presence of several other endogenous and exogenous regressors and the use of not too many instruments as suggested by Wooldridge (2002), Okui (2009) and Roodman (2009b). Fixed effects estimators are biased downward but also give significant results in all cases. Our estimates found in the region of within estimators and system GMM estimators provide a reasonable range for plausibly favourable effects of aid.

In the last line of Table 5 we report the optimal number of instruments found by Okui (2009) for the cases closest to ours. For column 1 there is no comparable case. In columns 2, 3, and 6 the optimal number suggested by Okui equals the number of linear instruments we find by way of starting with a low number of instruments and using the Sargan difference test for additional ones. In columns 4 and 5 the optimal number equals ours only if we include the instruments of lags with exponents two and three. As Okui employs only one lagged dependent variable and no other regressors his optimal numbers might have been different if he would have included lagged dependent variables with exponents two and three as we do and other exogenous or endogenous regressors such as our aid variable.

Finally, bi-variate loess-fit or kernel fit regressions for the aid variables and the dependent variables of all system GMM estimations of Table 2-4 confirm the sign of the slope of the regressions for the areas with most of the observations. Also here aid reduces illiteracy and increases life expectancy. This shows that our results are not driven by outliers.[32]

6. Conclusions and Outlook

This paper has shown in the survey that aid is effective in education and health, when captured by the indicators life expectancy and illiteracy. When earmarked aid is used,

[32] For reversed causality, sign and lag structures should be the opposite of what we find. Stepping (2012) finds that HIV has a positive impact and the Human Development Index (HDI) a negative significant impact on attracting aid in panel random effects estimates. If this has an impact on our estimates via the cross-section dimension, the effects of aid are even stronger than in our estimates.

disbursement data lead mostly to significant expected results, whereas commitment data do not. Panel data models, using lagged dependent variables, also yield expected, significant results unless commitment data are used.

In our own empirical research we find that lag structures suggest using the growth rates of life expectancy and illiteracy as the dependent variable. Development aid per capita in the form of growth rates has an impact on the growth rate of life expectancy. For illiteracy we find that either the level or the growth rate of aid has the expected effect. The results are obtained using fixed effects and system GMM estimators for more than 25 periods resulting in low biases for lagged dependent variables and only very weak endogeneity of the aid variables. Use of the inadequate OLS estimator frequently shows insignificant results for aid.

Taken together, this is a case for aid effectiveness and the continuation of development assistance. Nevertheless, there is of course room for improvement. The phenomenon of tying of aid still exists and this is closely related to the suspicion of aid being used as implicit export subsidy or side-payment in foreign-policy negotiations. Improving on these and other aspects that are subject of other debates remains a possibility for progress; this could improve the results of aid.

In a broader perspective, there is therefore a good justification to utilize more aid in the pursuit to attain the International Development Goals. The literature indicates though that there is much room for improvements, which future research should investigate, preferably using dynamic methods, whereas earlier cross-country regressions have shown the comparative effects. Progress in a country needs time and effects over time are different from those across countries.

Acknowledgements

I am grateful to Christof Gross for cooperation in the first phase of this paper. He made the first data set used here and contributed to the text. Recent developments in dynamic panel data econometrics required re-working the estimates in the second phase.

References

Andrews, D.W., Lu, B., 2001. Consistent model and moment selection procedures for GMM estimation with application to dynamic panel data models. *Journal of Econometrics* 101, 123-164.

Attanasio, O.P., Picci, L., Scorcu, A.E., 2000. Saving, growth, and investment: a macroeconomic analysis using a panel of countries. *Review of Economics and Statistics* 82, 182–211.

d'Aiglepierre, R. and L. Wagner (2010) Aid and Universal primary Education, CERDI, Etudes et Documents E2010.22.

Arellano and Bond (1991) Some tests of specification for panel data: Monte Carlo evidence and an application to employment equations, *Review of Economic Studies* 58, 277-297.

Arellano, M., Bover, O., 1995. Another look at the instrumental variable estimation of error-components models. *Journal of Econometrics* 68, 29–51.

Arndt, C., S. Jones, F. Tarp (2011) Aid Effectiveness, UNU-WIDER WP 20011/14, August.

Asteriou, D., Hall, S.G. (2011). Applied Econometrics, 4th ed. Palgrave Macmillan, New York.

Baltagi, B. H. (2008) Econometric Analysis of Panel Data, 4th ed., John Wiley, Chichester.

Bazzi, S. and Clemens, M.A. (2010) Blunt Instruments: A Cautionary Note on Establishing the Causes of Economic Growth, CGDEV WP 171, July.

Bhaumik, S.K., 2005. Does the World Bank have any impact on human development of the poorest countries? Some preliminary evidence from Africa. Economic Systems 29, 422-432.

Blundell, R. and Bond S. (1998). Initial conditions and moment restrictions in dynamic panel data models. *Journal of Econometrics* 87, 115–43.

Boone, P., 1996. Politics and the effectiveness of foreign aid. European Economic Review 40, 289–329.

Bun, M. J. G. and Windmeijer, F. (2010), The Weak Instrument Problem of the System GMM Estimator in Dynamic Panel Data Models," Econometrics Journal 13 (1): 95-126.

Burnside, C. and D. Dollar (1998) Aid, the Incentive Regime, and Poverty Reduction, Policy Research Working Paper 1937, June.

Burnside, C. and D. Dollar (2000) Aid, growth, the incentive regime, and poverty reduction. In: C.L. Gilbert and D.Vines, *The World Bank, Structure and Policies*, Cambridge University Press, Cambridge, UK, 210-227.

Burguet, R. and Soto, M., 2012. Measuring the child mortality impact of official aid for fighting infectious diseases, 2000-2010. Mimeo, March.

Chatelain, J.-B. and K. Ralf (2012) Spurious Regressions and Near-Multicollinearity, with an Application to Aid, policies and Growth. CES Working Papers 2012.78, November.

Chauvet, L, F. Gubert and S. Mesplé-Somps (2008) Are Remittances More Effective than Aid to Improve Child Health? An Empirical Assessment Using Inter and Intra-country Data, Paper prepared for the Annual Bank Conference on Development Economics, Cape Town, South Africa.

Collier, P. and D. Dollar (2002) Aid allocation and poverty reduction. *European Economic Review* 46, 1475–1500.

Davidson, R. and MacKinnon, J. (2004) Econometric Theory and Methods, Oxford University Press, Oxford.

Dreher, A., Nunnenkamp, P., Thiele, R., (2008) Does Aid for Education Educate Children? Evidence from Panel Data, *World Bank Economic Review* 22(2), 291-314.

Durlauf, S.N., P.A. Johnson, J.R.W. Temple (2005). Growth Econometrics. In: *Handbook of Economic Growth*. Eds.: P. Aghion and S. Durlauf. Amsterdam, North-Holland. 555-677.

Feeny, S. and B. Quattara (2013) The effects of health aid on child health promotion in developing countries: cross-country evidence, *Applied Economics* 45, 911-919.

Fielding, D., M. McGillivray and S. Torres (2006), A Wider Approach to Aid Effectiveness, UNU-WIDER Research paper 2006/23, February.

Gomanee, K., Girma, S., Morrissey, O. (2005a) Aid, Public Spending and Human Welfare: Evidence from Quantile Regressions, *Journal of International Development* 17, 299-309

Gomanee, K., Morrissey, O., Mosley, P., Verschoor, A. (2005b), Aid, Government Expenditure, and Aggregate, *World Development* 33, 355-70.

Greene, W. H. (2008) Econometric Analysis, 7th ed., Prentice-Hall Pearson, New Jersey.

Gross, C. (2003) Aids impact on education and health. MA thesis Maastricht University.

Gillanders, R. (2011) The Effects of Foreign Aid in Sub-Saharan Africa, UCD WP11/16, August.

Gyimah-Brempong, K. and E. Asiedu (2008) Aid and Human Capital Formation: Some Evidence, August. Paper for the African Development Bank/United Nations Economic Commission for Africa Conference on Globalization and Economic Development in Africa, Tunis, November 2008.

Hayakawa, K. and Pesaran M.H. (2012) Robust Standard Errors in Transformed Likelihood Estimation of Dynamic Panel Data Models. CESIFO WORKING PAPER NO. 3850.

Hudson, J. and Mosley, P.: Aid Policies and Growth: In Search of the Holy Grail, 2001, *Journal of International Development*, 13, 1023-38.

Masud, N. and B. Yontcheva (2005) Does Foreign Aid Reduce Poverty? Empirical Evidence from Nongovernmental and bilateral Aid, IMF Working paper WP/05/100, May.

Michaelowa, K. (2004) Aid Effectiveness Reconsidered - Panel Data Evidence for the Education Sector. HWWA DISCUSSION PAPER 264, February.

Mosley, P., J. Hudson and A. Verschoor (2004), Aid, Poverty Reduction and the 'New Conditionality', *The Economic Journal* 114, F217-F243.

Mukherjee, D. and E.T. Kizhakethalckal (2013), Empirics of health-aid, education and infant mortality: a semiparametric study, *Applied Economics* 45, 3137-3150.

Okui, R. (2009) The optimal choice of moments in dynamic panel data models. *Journal of Econometrics* 151 (2009) 1-16.

Riddel, A. (2012) The Effectiveness of foreign Aid to Education, UNU-WIDER Working Paper 2012/75.

Roodman, D., (2009a), How to do xtabond2: an introduction to "difference" and "system" GMM in stata. STATA JOURNAL Vol. 9, Issue 1, pp. 86 – 136.

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

Smith, R.P. and A.-M. Fuentes (2010) Panel Time-Series, cemmap course April 2010. Download 24 Aug 2011.

Soto, M. (2009) System GMM estimation with small sample, Institut d'Anàlisi Econòmica, Barcelona, July.

Stepping, K. (2012) Do poor health conditions lead to higher allocation of development assistance. MAGKS Working Paper 30-2012.

Verschoor, A. and Kalwij, A. (2006) Aid, Social Policies and Pro-Poor Growth, *Journal of International Development* 18, 519 – 532.

White, H. (2001) Will the new aid agency help promote poverty reduction? *Journal of International Development* 13, 1057-1070.

Williamson, C. (2008) Foreign Aid and Human Development: The Impact of foreign Aid to the Health Sector, *Southern Economic Journal* 75(1), 188-207.

Wilson, S.E. (2011) Chasing Success: Health Sector Aid and Mortality, *World Development* 39 (11), 2032-2043.

Wolf, S. (2007), Dies Aid Improve Public Service Delivery? *Review of World Economics* 143 (4), 650 - 672.

Wooldridge, J. M. (2002) Econometric Analysis of Cross Section and Panel Data, MIT Press, Cambridge, Massachusetts; London England.

World Bank, World Development Indicators. Several editions. Washington.

Ziesemer, T. (2011a), Growth with Endogenous Migration Hump and the Multiple, Dynamically Interacting Effects of Aid in Poor Developing Countries, *Applied Economics* 43, 4865-4878.

Ziesemer, T. (2011b), What Changes Gini Coefficients of Education? On the dynamic interaction between education, its distribution and growth, UNU-MERIT WP 2011-053.

Appendix

List of countries

East Asia and Pacific: Cambodia; Indonesia; Korea, Dem. Rep.; Lao PDR; Mongolia; Myanmar; Papua New Guinea, Solomon Islands; Vietnam.

Europe and Central Asia: Armenia; Azerbaijan; Georgia; Kyrgyz Republic; Moldova; Tajikistan; Ukraine; Uzbekistan.

Latin America and Caribbean: Haiti, Nicaragua.

Middle East and North Africa: Yemen, Rep..

South Asia: Afghanistan, Bangladesh, Bhutan, India, Nepal, and Pakistan.

Sub-Saharan Africa: Angola; Benin; Burkina Faso; Burundi; Cameroon; Central African Republic; Chad; Comoros; Congo, Dem. Rep.; Congo, Rep.; Cote d'Ivoire; Equatorial Guinea; Eritrea; Ethiopia; Gambia, The; Ghana; Guinea; Guinea-Bissau; Kenya; Lesotho; Liberia; Madagascar; Malawi; Mali; Mauritania; Mozambique; Niger; Nigeria; Rwanda; Sao Tome and Principe; Senegal; Sierra Leone; Somalia; Sudan; Tanzania; Togo; Uganda; Zambia; Zimbabwe.

Table A.1: Descriptive Statistics, individual samples

(a) Data for 65 countries, 1960-2000 in five-year averages

	AID	GDP	HEALTH	ILL	LIFE	PEE	RURAL
Mean	41.58	447.62	4.30	52.47	50.12	4.00	74.32
Median	29.64	350.53	4.05	58.33	48.14	3.09	77.10
Maximum	478.78	2492.38	12.68	94.25	73.48	41.78	97.88
Minimum	0.55	95.46	1.63	0.42	32.45	0.02	30.56
Std. Dev.	46.82	336.17	1.83	26.38	9.50	4.23	15.33
Skewness	3.75	2.63	1.48	-0.55	0.71	5.55	-0.74
Kurtosis	26.34	12.51	6.44	2.26	2.70	42.98	2.93
Jarque-Bera	10463.26	1797.62	121.57	26.52	42.17	20807	45.44
Probability	0	0	0	2E-06	0	0	0
Sum	17380.1	163382.1	610.2	18732.6	24105.8	1160.6	37234.5
Sum Sq. Dev.	914223.7	41136108.0	470.4	247801	43356.2	5161.3	117465
Observations	418	365	142	357	481	290	501

(b) Data for 65 countries, 1960-2001, yearly

	AID	GDP	HEALTH	ILL	LIFE	PEE	RURAL
Mean	29.84	432.17	4.17	49.95	50.49	3.88	74.69
Median	15.40	355.50	3.90	53.65	48.20	3.09	77.20
Maximum	638.00	2110.00	12.20	94.30	74.40	41.80	97.80
Minimum	0.00	49.30	0.86	0.38	31.20	0.27	32.00
Std. Dev.	42.79	278.94	1.69	25.51	10.09	3.57	15.20
Skewness	4.71	1.96	1.09	-0.45	0.63	5.14	-0.72
Kurtosis	42.92	8.48	4.93	2.23	2.43	42.60	2.87
Jarque-Bera	164506	3676.76	209.00	98.45	94.36	52990	230.26
Probability	0	0	0	0	0	0	0
Sum	70031.7	841002.7	2462.2	84707.9	59574.4	2951.3	199121
Sum Sq. Dev.	4295863	151000000.0	1691.1	1103141	119957	9700.0	616055
Observations	2347	1946	591	1696	1180	760	2666

(c) Data for 65 countries, 1960-2010, yearly

	AID	GDP	HEALTH	ILL	LIFE	PEE	RURAL
Mean	67.89	455.22	5.52	47.99	51.24	4.09	72.61
Median	47.33	335.74	5.18	51.27	49.84	3.39	74.62
Maximum	928.13	8811.21	19.31	94.25	73.78	49.52	98.00
Minimum	-0.18	57.78	0.01	0.00	26.82	0.42	31.90
Std. Dev.	81.17	518.75	2.45	26.27	9.54	3.70	15.33
Skewness	3.36	9.33	1.52	-0.35	0.27	7.00	-0.58
Kurtosis	20.37	128.59	7.01	2.05	2.30	71.75	2.61
Jarque-Bera	43147.03	1629650.00	1060.34	90.04	86.50	120801	211.08
Probability	0	0	0	0	0	0	0
Sum	202586	1104367	5555	75244	135889	2406	244412
Sum Sq. Dev.	19652759	653000000	6023	1081497	241433	8058	790841
Observations	2984	2426	1006	1568	2652	589	3366

The three panels differ in terms of their base years for some variables.

Table A.2	**Preliminary panel fixed effects estimates**					
Dependent variable	*LOG(LIFE)-LOG(LIFE(-5))*			*ILL-ILL(-5)*		
Regressors	(1)	(2)	(3)	(4)	(5)	(6)
C	-0.019	-0.657	0.146	4.399	3.429	-2.363
	(0.015)	(0.000)	(0.000)	(0.001)	(0.000)	(0.004)
HEALTH-HEALTH(-5)	0.121	0.024	-	-	-	-
	(0.002)	(0.015)	-	-	-	-
HEALTH^2-HEALTH(-5)^2	-0.015	-0.003	-	-	-	-
	(0.002)	(0.013)	-	-	-	-
HEALTH(-1)	-	-	**-0.003**	-	-	-
	-	-	(0.092)	-	-	-
LOG(LIFE)-LOG(LIFE(-1))				-2.235		
				(0.023)		
LOG(LIFE(-5))-LOG(LIFE(-10))	-29.209	-12.330	-0.182	-	-	-2.235
	(0.000)	(0.001)	(0.033)	-	-	(0.013)
LOG(LIFE(-5))^2-LOG(LIFE(-10))^2	3.773	1.581	-	-	-	-
	(0.000)	(0.001)	-	-	-	-
LOG(AID(-0))-LOG(AID(-5))	-	0.017	0.011	-	-	-
	-	(0.052)	(0.000)	-	-	-
(LOG(AID)-LOG(AID(-1)))^2	-	-	-	-0.250	-	-
	-	-	-	(0.000)	-	-
LOG(AID(-1))^2-LOG(AID(-6))^2	-	-0.003	-	-	-	-
	-	(0.007)	-	-	-	-
LOG(AID(-5))-LOG(AID(-10))	0.025	-	0.007	-	-	-
	(0.074)	-	(0.000)	-	-	-
(LOG(AID(-5))-LOG(AID(-10)))^2	-	-	-	-	-0.016	-0.189
	-	-	-	-	(0.047)	(0.006)
NINET*LOG(AID(-1))-LOG(AID(-2))	-	-	-	-	-0.025	-
	-	-	-	-	(0.052)	-
NINET*LOG(AID(-5))-LOG(AID(-10))	-	-	-	-0.130	-	-
	-	-	-	(0.001)	-	-
RURAL(-0)	-	0.010	**-0.001**	-0.094	-0.052	-
	-	(0.000)	(0.001)	(0.000)	(0.000)	-
LOG(GDP(-1))-LOG(GDP(-6))	-	0.042	0.013	-	-	-
	-	(0.028)	(0.067)	-	-	-
(ILL(-5))-(ILL(-10))	-	-	-	0.337	0.625	0.296
	-	-	-	(0.000)	(0.000)	(0.011)
(ILL(-10))-(ILL(-15))	-	-	-	-	0.294	-
	-	-	-	-	(0.002)	-
PEE(-5)	-	-	-	-	-	-1.194
	-	-	-	-	-	(0.001)
LOG(PEE(-5))	-	-	-	-0.469	-0.126	-
	-	-	-	(0.005)	(0.001)	-
LOG(PEE(-10))	-	-	-	-0.382	-	0.653
	-	-	-	(0.012)	-	(0.014)
LOG(PEE(-5))^2	-	-	-			1.796
	-	-	-			(0.001)
LOG(PEE(-10))^2	-	-	-			-0.372
	-	-	-			(0.007)
Period	1990-2000	1995-2000	1996-2010	1975-2000	1985-2001	1980-2009
Data	5-year ave.	yearly	yearly	5-year ave.	yearly	yearly
Countries/periods (N/T)	42/2	54/5	48/15	36/5	46/17	20/7
total observations	73	125	680	126	438	39
Adjusted R-squared	0.821	0.864	0.660	0.948	0.981	0.995
S.E. of regression	0.025	0.021	0.029	0.399	0.239	0.148
Mean dependent variable	-0.002	-0.002	0.033	-4.979	-4.666	-5.111
Notes						
p-values in parentheses. Fixed effects estimations without any instruments.						
Cross-section fixed effects and weights (PCSE) standard errors & covariance (d.f. corrected) in all regressions.						
Lag notation for yearly variables. In regressions (1) and (4) the lag notations -5, -10 can be replaced by -1,-2 in terms of 5-year periods.						
When adding time dummies to equation (2) 'rural' becomes insignificant;other results change only marginally.						
When adding time dummies to equation (3) the growth rate of the GDP per capita becomes insignificant; 'rural' changes sign if we take the growth rate out, and the constant becomes insignificant, but other results change only marginally. We have added a '1 'to the aid variable in this equation in order to avoid a log of a non-positice variable. Time dummies do not change sign or significance for equation (5).						

Table 1	**Literature structure**									
Publication	*social indicator*	*aid form (a)*	*com., disb. (b)*	*countr*	*years*	*ldv*	*est. Meth.*	*exp.sign*	*signif.*	*Remarks*
Arndt et al. (2011)	life expectancy	total, pc	-	58	1970-2007	no	IPWLS	yes	yes	multi-eq. cross sec. model
Bhaumik (2005)	infant mortality	total	-	36-7	1990-2002	no	FELS	yes	yes	variables differenced
	primary completion	total	-	36-7	1990-2002	no	FELS	yes	yes	variables differenced
Boone (1996)	(c)	total aid/GNP	-	96	1970-1990	no	OLS, IV, FELS	yes	no	10 year averages of data
Burguet, Soto (2012)	under-5 mortality	infect. disease aid	disbursed	130	2000-2010	no	2SLS	yes	yes	yearly data
Burnside, Dollar (1998, 2000)	infant mortality	total*policy	-	56	1970-1993	no	2SLS	yes	yes	4 year averages
Chauvet et al. (2008)	u5 & infant mort.	health aid	disbursed	98	1987-2004	no	2SLS	yes	yes	3 year average
D'Aiglepierre, Wagner (2010)	prim. Compl. Rate	aid f. Prim. Educ.	commit., disb.	46-88	1999-2007	no	FELS, FEIV	yes	yes	3 year average
Dreher et al. (2008)	primary enrolm.	educ aid, total	commit., disb.	94	1970-2004	yes	system GMM	yes	yes, no	5 year averages,
Feeny, Quattara (2013)	immunizations	health aid	disbursed	109	1990-2005	no	basic, sysGMM	yes	yes	yearly
Fielding et al. (2006)	infant mortality	total, pc	-	48	-	no		yes	yes	cross-section regr.
Fielding et al. (2006)	schooling	total, pc	-	48	-	no		yes	no	quintile and survey years
Gomanee et al. (2005a)	infant mortality	total aid/GDP	-	38	1980-1998	no	OLS, quantile	yes	yes	3 and 4 year average
Gomanee et al. (2005b)	infant mortality	total aid/GDP	-	104	1980-2000	no	FELS	yes	yes	4 and 5 year average
Gillanders (2011)	life expectancy	total aid pc	-	31	1973-2005	yes	PFELS	yes	yes	PVAR model
Gross (2003)	life expect., literacy	total aid pc	-	65	1960-2000	yes	FELS	yes	yes	5 year averages,
Gyimah-Brempong, Asiedu (2008)	prim.compl.rate	earmarked	disbursed	90	1990-2004	yes	Arellano-Bond	yes	yes	3 year average
Gyimah-Brempong, Asiedu (2008)	infant mortality	earmarked	disbursed	90	1990-2004	yes	Arellano-Bond	yes	yes	3 year average
Masud, Yontcheva (2005)	illiteracy	bilateral, NGO aid	committed	54-76	1990-2001	no	random effects	no	no	yearly data
Masud, Yontcheva (2005)	infant mortality	NGO	disbursed ?	49-58	1990-2001	no	fixed, random eff.	yes	yes/no	yearly data
Michaelowa (2004)	primary enrolm.	education aid	disbursed	42-76	1970-2000	yes	Arellano-Bond	yes	yes	annual or 5 year averages
Mishra, Newhouse (2009)	infant mortality	health aid, total	commited	118	1973-2004	yes	system GMM	yes	yes, no	5 year averages,
Mukherjee, Kizhakethalckal (2013)	infant mortality	health aid	disbursed	110	1978-2001	no	semiparametric	yes	yes, no	4 year averages
Williamson (2008)	5 health indicators	earmarked, pc	committed (f)	208	1973-2004	no	FE, IV	mixed	no	5 year averages,
Wilson 2011	u5, inf., life exp.	Dev. Ass.Health	committed	84	1975-2005	yes	Arellano-Bond	mixed	no	5 year averages,
Wolf (2007)	(d)	(e)	com.; disb.?(f)	41-109	1980-2002	no	OLS	mixed	mixed	40-110 observations
Ziesemer (2011a)	literacy	total aid/GDP	-	30	1985-2004	yes	FELS	yes	yes	yearly data, var. differenc.

(a) The expressions total, overall and aggregte aid are used synonymously in the literature. Most papers do not report whether total aid is disbursed or committed.

(b) The distinction between disbursed and committed aid appears in the literature only for earmarked aid, not for overall aid.

(c) Infant mortality, primary schooling, life expectancy,

(d) Sanitation, water, infant and under-5 mortality, primary completion rates and youth literacy

(e) Aid/GNI and its coefficient of variation, earmarked aid and its interaction with control of corruption

(f) This is also based on information in Michaelowa (2004), who state that there is information on disbursements only for 42 countries.

Table 2	**Results for life expectancy until 2000**						
Dependent variable	*LOG(LIFE)-LOG(LIFE(-1))*				*LOG(LIFE)-LOG(LIFE(-5))*		
Estimation Method	FELS	GMMSYS	OLS		FELS	GMMSYS	OLS
Regressors	(1)	(2)	(3)	*Regressors*	(4)	(5)	(6)
Constant	-0.019	-	-0.027	Constant	0.011	-	-0.002
	(0.015)	-	(0.000)		(0.021)	-	(0.618)
LOG(LIFE(-1))-LOG(LIFE(-2))	-29.209	-25.992	-22.405	LOG(LIFE(-5))-LOG(LIFE(-10))	0.475	0.637	0.790
	(0.000)	(0.0004)	(0.000)		(0.000)	(0.007)	(0.000)
LOG(LIFE(-1))^2-LOG(LIFE(-2))^2	3.773	3.331	3.000	LOG(LIFE(-10))-LOG(LIFE(-15))	-0.295	-0.379	-0.188
	(0.000)	(0.0006)	(0.000)		(0.001)	(0.012)	(0.027)
LOG(AID(-1))-LOG(AID(-2))	0.025	0.027	-0.002	(LOG(LIFE(-5))-LOG(LIFE(-10)))^2	1.697	3.489	1.902
	(0.074)	(0.0073)	(0.815)		(0.000)	(0.000)	(0.000)
HEALTH-HEALTH(-1)	0.121	0.132	0.016	(LOG(LIFE(-5))-LOG(LIFE(-10)))^3	-8.224	-9.219	-10.121
	(0.002)	(0.000)	(0.132)		(0.000)	(0.047)	(0.000)
HEALTH^2-HEALTH(-1)^2	-0.015	-0.017	-0.002	LOG(AID)-LOG(AID(-5))	0.010	0.018	0.007
	(0.002)	(0.000)	(0.029)		(0.000)	(0.000)	(0.001)
Period	1990-2000	1990-2000	1990-2000		1975-2000	1977-2000	1975-2000
Data	5-year ave.	5-year ave.	5-year ave.		yearly	yearly	yearly
Countries/periods (N/T)	42/2	31/1	42/2		63/11	58/10	63/11
total observations	73	31	73		593	520	593
Adjusted R-squared	0.821	-	0.565		0.447	-	0.367
S.E. of regression	0.025	0.025	0.039		0.039	0.043	0.042
Hansen J-stat., p(J)	-	10.3, 0.036	-		-	40/0.29	-
Notes							

Cross-section fixed effects and weights (PCSE) standard errors & covariance (d.f. corrected) in regression (1)-(3) and Period SUR in (4)-(6).

Orthogonal deviations for GMMSYS. 2SLS instrument weighting matrix Time dummies in eq. (4)-(6).

Instrument list for GMMSYS (2): HEALTH(-0)-HEALTH(-1), HEALTH(-0)^2-HEALTH(-1)^2,LOG(LIFE(-2))-LOG(LIFE(-3)), LOG(LIFE(-2))^2-LOG(LIFE(-3))^2, LOG(LIFE(-3))-LOG(LIFE(-4)),LOG(LIFE(-3))^2-LOG(LIFE(-4))^2 ,LOG(LIFE(-4))-LOG(LIFE(-5)), LOG(LIFE(-4))^2-LOG(LIFE(-5))^2, LOG(AID(-1))-LOG(AID(-2)).

Instrument specification for eq. (5) : @DYN(LOG(LIFE)-LOG(LIFE(-5)),-7,-7), @DYN((LOG(LIFE)-LOG(LIFE(-5)))^3,-7,-7), @DYN((LOG(LIFE)-LOG(LIFE(-5)))^3,-7,-8) @DYN(LOG(LIFE)-LOG(LIFE(-5)),-15,-15), LOG(AID(-1))-LOG(AID(-6)), period dummies, c. Hansen-Sargan diff. p-val. =0.249 for lag 8 in the cubic term.

Table 3	Results for illiteracy until 2001						
Dependent variable	*LOG(ILL)-LOG(ILL(-1))*				*LOG(ILL)-LOG(ILL(-5))*		
Estimation Method	FELS	GMMSYS	OLS		FELS	GMMSYS	OLS
Regressors	(1)	(2)	(3)	*Regressors*	(4)	(5)	(6)
Constant	-0.050	-	-0.017	Constant	-0.064	-	-0.005
	(0.000)	-	(0.000)		(0.000)	-	(0.194)
LOG(ILL(-1))-LOG(ILL(-2))	0.572	0.965	1.008	LOG(ILL(-5))-LOG(ILL(-10))	0.213	0.493	0.919
	(0.000)	(0.000)	(0.000)		(0.021)	(0.051)	(0.000)
NINETIES*(LOG(AID))	-0.003	-0.001	0.001	$(\mathrm{LOG(ILL(-10))-LOG(ILL(-15))})^2$	-1.421	-2.112	0.118
	(0.000)	(0.086)	(0.045)		(0.027)	(0.005)	(0.741)
				$(\mathrm{LOG(AID(-5))-LOG(AID(-10))})^2$	-0.001	-0.002	0.000
					(0.005)	(0.018)	(0.465)
				LOG(ILL(-10))-LOG(ILL(-15))	0.125	-0.268	0.185
					(0.531)	(0.300)	(0.122)
Period	1975-2000	1985-2000	1975-2000		1985-2001	1991-2001	1985-2001
Data	5-year ave.	5-year ave.	5-year ave.		yearly	yearly	yearly
Countries/periods (N/T)	51/5	47/3	51/5		49/17	48/11	49/17
total observations	230	132	230		792	516	792
Adjusted R-squared	0.979	-	0.946		0.977	-	0.950
S.E. of regression	0.009	0.007	0.015		0.009	0.009	0.013

Notes

Cross-section fixed effects and weights (PCSE) standard errors & covariance (d.f. corrected) in regressions (1)-(3).

Orthogonal deviations for GMMSYS. 2SLS instrument weighting matrix.

Panel version of Durbin-Wu-Hausman test by Davidson McKinnon using OLS shows no endogeneity for the aid variable. As instruments are lagged dependent though, we also carry out the test in terms of fixed effects and GMMSYS. These two versions do indicate endogeneity. Instrument specification for equation (2): (ILL(-2))-(ILL(-3)), LOG(AID(-1))*NINETIES, c. If the regressor is used instead of lagged aid the coefficients in equation (2) are 0.916, -0.0014.

With instrument rank equal to the number of estimated parameters there is no overidentification and the Hansen J-statistic is zero.

Time fixed effects and period SUR (PCSE) standard errors & covariance (d.f. corrected) for regressions (4)-(6).

Instrument specification for equation (5): LOG(ILL(-10))-LOG(ILL(-15)), $(\mathrm{LOG(ILL(-10))-LOG(ILL(-15))})^2$, $(\mathrm{LOG(AID(-5))-LOG(AID(-10))})^2$, LOG(ILL(-15))-LOG(ILL(-20)), period dummies, c. Second-order serial correlation of ten or fifteen period lagged residuals on the current or 5-year lagged residuals cannot be tested because there are two little data.

The last regressor in the table is added in spite of its insignifcance in order to avoid serial corrleation bias (Greene 2008). In case of using cross-section weights instead of Period SUR it is significant. Period SUR is used though as orthogonal deviations always imply first-order serial correlation (Roodman 2006).

Table 4	**The impact of aid on life expectancy and illiteracy**						
Dependent variable	*LOG(LIFE)-LOG(LIFE(-5))*				*LOG(ILL)-LOG(ILL(-5))*		
Estimation Method	FELS	GMMSYS	OLS		FELS	GMMSYS	OLS
Regressors	(1)	(2)	(3)	*Regressors*	(4)	(5)	(6)
Constant	0.027	-	0.022	Constant	0.002	-	0.001
	(0.000)	-	(0.000)		(0.738)	-	(0.868)
LOG(LIFE(-5))-LOG(LIFE(-10))	0.588	0.756	0.717	LOG(ILL(-1))-LOG(ILL(-6))	2.202	2.070	1.710
	(0.000)	(0.000)	(0.000)		(0.000)	(0.000)	(0.000)
$(LOG(LIFE(-5))-LOG(LIFE(-10)))^2$	0.563	2.482	0.431	LOG(ILL(-2))-LOG(ILL(-7))	-1.273	-1.138	-0.698
	(0.000)	(0.000)	(0.000)		(0.000)	(0.008)	(0.059)
$(LOG(LIFE(-5))-LOG(LIFE(-10)))^3$	-4.125	-6.683	-4.736	$LOG(1+AID(-10)/POP(-10))^2$	-0.001	-0.00063	-0.000013
	(0.000)	(0.000)	(0.000)		(0.003)	(0.004)	(0.935)
LOG(LIFE(-10))-LOG(LIFE(-15))	-0.492	-0.569	-0.451				
	(0.000)	(0.000)	(0.000)				
LOG(1+AID/POP)-LOG(1+AID(-5)/POP(-5))	0.007	0.011	0.006				
	(0.003)	(0.057)	(0.008)				
Period	1975-2010	1981-2010	1975-2010		1977-2003	1979-2003	1977-2003
Countries/periods (N/T)	52/36	52/30	52/36		45/27	42/25	45/27
total observations	1723	1447	1723		1035	951	1035
Adj.R-sq.	0.441	-	0.372		0.918	-	0.752
S.E. of regression	0.039	0.050	0.042		0.020	0.021	0.035

Notes

In all regressions: Yearly data, time-fixed effects, period SUR (PCSE) standard errors & covariance (d.f. corrected)

GMMSYS uses the orthogonal deviation method with 2SLS instrument weighting matrix.

Instrument specification for equation (2): c, LOG(LIFE(-7))-LOG(LIFE(-12)), $(LOG(LIFE(-7))-LOG(LIFE(-12)))^2$, $(LOG(LIFE(-7))-LOG(LIFE(-12)))^3$, LOG(LIFE(-15))-LOG(LIFE(-20)), LOG(1+AID(-1)/POP(-1))-LOG(1+AID(-6)/POP(-6)), time dummies for all periods.

Instrument specification for equation (5): LOG(ILL(-2))-LOG(ILL(-7)), LOG(ILL(-3))-LOG(ILL(-8)) , $LOG(1+AID(-10)/POP(-10))^2$, time dummies for all periods.

In regressions (4) and (5) a linear or a cubic term would also show a significantly negativ sign. When all three are used together collinearity generates low t-values and significance levels.

With instrument rank equal to the number of estimated parameters there is no overidentification and the Hansen J-statistic is zero.

Table 5	System GMM properties in second generation Monte Carlo studies					
Depend. variable	*dLOG(LIFE)*	*dLOG(LIFE)*	*dlog(ill)*	*dlog(ill)*	*dLOG(LIFE)*	*dlog(ill)*
Equation	Table 2, eq.(2)	Table 2, eq. (5)	Table 3, eq.(2)	Table 3, eq. (5)	Table 4, eq.(2)	Table 4, eq.(5)
Stdev fe (a)	0.075	0.019	0.006	0.021	0.023	0.008
s.e.e. (b)	0.025	0.043	0.007	0.009	0.050	0.021
var ratio (c)	8.822	0.202	0.626	5.214	0.213	0.132
Bias (d) from vr	na (g); positive	-0.01 (h)	0.05 (i)	-0.035;-0.044 (j)	na (k); negative	-0.02 (l)
Bias ? 1/T	irr (T=1)	slightly positive	positive	positive	positive	slightly neg.
coeff. Ar(1) aid (e)	irr	0.59	0.93	irr	0.656	irr
corr.coeff. Resid (f)	irr	0.069	-0.095	irr	-0.022	irr
Aid endogen. bias	irr	slightly negative	negative	irr	slightly negative	irr
Opt. no. of instr.lags	na	2	1	4 (m)	5	2

Notes

(a) Standard deviation of fixed effects

(b) Standard error of estimation

(c) ratio of previous two lines squared: stdev/see)^2

(d) Intuitive value close to Monte Carlo results according to tables indicated in the notes below focusing on variance ratio, coeff. of lag.dep. variable, and T.

(e) Coefficient from running regression of regressors other than the lagged dependent variable on its instruments; if several lags are used we present the sum of coefficients.

(f) Correlation coefficient from residuals in regression and residuals in regression as in (e).

(g) Not available. Okui (2009) investigates T=10 or 25; Bun/Windmeijer (2010) T=6 or 15; Hayakawa/Pesaran (2012) T=5,10,15.

(h) Bun/Windmeijer for coeff.of lag.dep. 0.4 and no other regressors, variance ratio of 0.25, T=6.

(i) Hayakawa/Pesaran (2012) for coeff.of lag.dep. 0.9 and one exogenous regressor, variance ratio of 1, T=5.

(j) Okui (2009) for coeff.of lag.dep. 0.5, no exogenous regr, regressors, variance ratio of 1 and 10 respectively, T=10.

(k) Okui (2009) has T=25, but no variance ratios below unity. Bun/Windmeijer suggest a small negative bias.

(l) The ratio of observations to cross-section is about 20; for T=15,coeff.of lag.dep. 0.8 and a variance ratio of 0.25 in Bun/Windmeijer (2010) ,

(m) Okui (2009) suggests four lags for a variance ratio of 10, but ours is only 5. He does not cover the case of higher exponents of lagged dependent variables.

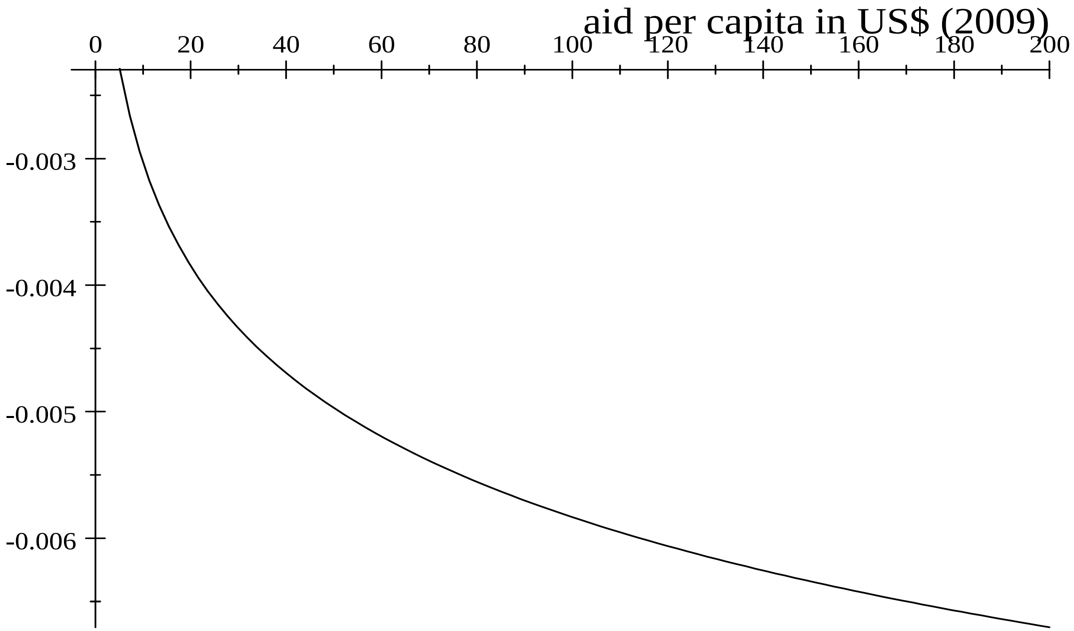

Figure 1 The effect of development aid per capita on the five-year growth rate of illiteracy

List of abbreviations

AB-GMM	GMM version of Arellano-Bond.
DAC	development assistance committee
DPT	Diphtheria-Pertussis-Tetanus
DGP	data generating process
FELS	fixed-effects least squares
GDP	gross domestic product
GNI	gross national income
GMM	General Method of Moments
HDI	Human Development Index
HIV	Human immunodeficiency virus
IDA	infectious-disease aid
IPWLS	Inverse Probability Weighted Least Squares
Ldv	lagged dependent variable
LIML	limited information maximum likelihood
NGO	non-governmental organisation
OECD	Organisation for Economic Cooperation and Development
SSA	Sub-Saharan Africa
STD	sexually transmitted diseases
US	United States of America

The UNU-MERIT WORKING Paper Series

2012-01 *Maastricht reflections on innovation* by Luc Soete
2012-02 *A methodological survey of dynamic microsimulation models* by Jinjing Li and Cathal O'Donoghue
2012-03 *Evaluating binary alignment methods in microsimulation models* by Jinjing Li and Cathal O'Donoghue
2012-04 *Estimates of the value of patent rights in China* by Can Huang
2012-05 *The impact of malnutrition and post traumatic stress disorder on the performance of working memory in children* by Elise de Neubourg and Chris de Neubourg
2012-06 *Cross-national trends in permanent earnings inequality and earnings instability in Europe 1994*-2001 by Denisa Maria Sologon and Cathal O'Donoghue
2012-07 *Foreign aid transaction costs* by Frieda Vandeninden
2012-08 *A simulation of social pensions in Europe* by Frieda Vandeninden
2012-09 *The informal ICT sector and innovation processes in Senegal* by Almamy Konté and Mariama Ndong
2012-10 *The monkey on your back?! Hierarchical positions and their influence on participants' behaviour within communities of learning* by Martin Rehm, Wim Gijselaers and Mien Segers
2012-11 *Do Ak models really lack transitional dynamics?* by Yoseph Yilma Getachew
2012-12 *The co-evolution of organizational performance and emotional contagion* by R. Cowan, N. Jonard, and R.Weehuizen
2012-13 *"Surfeiting, the appetite may sicken": Entrepreneurship and the happiness of nations* by Wim Naudé, José Ernesto Amorós and Oscar Cristi
2012-14 *Social interactions and complex networks* by Daniel C. Opolot
2012-15 *New firm creation and failure: A matching approach* by Thomas Gries, Stefan Jungblut and Wim Naudé
2012-16 *Gains from child-centred Early Childhood Education: Evidence from a Dutch pilot programme* by Robert Bauchmüller
2012-17 *Highly skilled temporary return, technological change and Innovation: The Case of the TRQN Project in Afghanistan* by Melissa Siegel and Katie Kuschminder
2012-18 *New Technologies in remittances sending: Opportunities for mobile remittances in Africa* Melissa Siegel and Sonja Fransen
2012-19 *Implementation of cross-country migration surveys in conflict-affected settings: Lessons from the IS Academy survey in Burundi and Ethiopia* by Sonja Fransen, Katie Kuschminder and Melissa Siegel
2012-20 *International entrepreneurship and technological capabilities in the Middle East and North Africa* by Juliane Brach and Wim Naudé
2012-21 *Entrepreneurship, stages of development, and industrialization* by Zoltan J. Ács and Wim Naudé
2012-22 *Innovation strategies and employment in Latin American firms* by Gustavo Crespi and Pluvia Zuniga
2012-23 *An exploration of agricultural grassroots innovation in South Africa and implications for innovation indicator development* by Brigid Letty, Zanele Shezi and Maxwell Mudhara
2012-24 *Employment effect of innovation: microdata evidence from Bangladesh and Pakistan* by Abdul Waheed

2012-25 *Open innovation, contracts, and intellectual property rights: an exploratory empirical study* by John Hagedoorn and Ann-Kristin Ridder
2012-26 *Remittances provide resilience against disasters in Africa* by Wim Naudé and Henri Bezuidenhout
2012-27 *Entrepreneurship and economic development: Theory, evidence and policy* by Wim Naudé
2012-28 *Whom to target - an obvious choice?* by Esther Schüring and Franziska Gassmann
2012-29 *Sunk costs, extensive R&D subsidies and permanent inducement effects* by Pere Arqué-Castells and Pierre Mohnen
2012-30 *Assessing contingent liabilities in public-private partnerships (PPPs)* by Emmanouil Sfakianakis and Mindel van de Laar
2012-31 *Informal knowledge exchanges under complex social relations: A network study of handloom clusters in Kerala, India* by Robin Cowan and Anant Kamath
2012-32 *Proximate, intermediate and ultimate causality: Theories and experiences of growth and development* by Adam Szirmai
2012-33 *Institutions and long-run growth performance: An analytic literature review of the institutional determinants of economic growth* by Richard Bluhm and Adam Szirmai
2012-34 *Techniques for dealing with reverse causality between institutions and economic performance* by Luciana Cingolani and Denis de Crombrugghe
2012-35 *Preliminary conclusions on institutions and economic performance* by Denis de Crombrugghe and Kristine Farla
2012-36 *Stylized facts of governance, institutions and economic development. Exploring the institutional profiles database* by Bart Verspagen
2012-37 *Exploring the Panel Components of the Institutional Profiles Database (IPD)* by Luciana Cingolani and Denis de Crombrugghe
2012-38 *Institutions and credit* by Kristine Farla
2012-39 *Industrial policy for growth* by Kristine Farla
2012-40 *Explaining the dynamics of stagnation: An empirical examination of the North, Wallis and Weingast approach* by Richard Bluhm, Denis de Crombrugghe and Adam Szirmai
2012-41 *The importance of manufacturing in economic development: Past, present and future perspectives* by Wim Naudé and Adam Szirmai
2012-42 *Lords of Uhuru: the political economy of elite competition and institutional change in post-independence Kenya* by Biniam Bedasso
2012-43 *Employment and wages of people living with HIV/AIDS* by Pilar García-Gómez, José M. Labeaga and Juan Oliva
2012-44 *Prescriptions for network strategy: Does evidence of network effects in cross-section support them?* by Joel A.C. Baum, Robin Cowan and Nicolas Jonard
2012-45 *Perspectives on human development theory in democracy promotion: A comparison of democracy promotion programmes in Egypt through the lenses of classical and revised modernisation theory* by Inger Karin Moen Dyrnes
2012-46 *Nonlinearities in productivity growth: A semi-parametric panel analysis* by Théophile T. Azomahou, Bity Diene and Mbaye Diene
2012-47 *Optimal health investment with separable and non-separable preferences* by Théophile T. Azomahou, Bity Diene, Mbaye Diene and Luc Soete
2012-48 *Income polarization and innovation: Evidence from African economies* by Théophile T. Azomahou and Mbaye Dien

2012-49 *Technological capabilities and cost efficiency as antecedents of foreign market entry* by Fabrizio Cesaroni, Marco S. Giarratana and Ester Martínez-Ros
2012-50 *Does the internet generate economic growth, international trade, or both?* by Huub Meijers
2012-51 *Process innovation objectives and management complementarities: patterns, drivers, co-adoption and performance effects* by Jose-Luis Hervas-Oliver, Francisca Sempere-Ripoll and Carles Boronat-Moll
2012-52 *A systemic perspective in understanding the successful emergence of non-traditional exports: two cases from Africa and Latin America* by Michiko Iizuka and Mulu Gebreeyesus
2012-53 *Determinants of quadic patenting: Market access, imitative threat, competition and strength of intellectual property rights* Can Huang and Jojo Jacob
2012-54 *Envy and habits: Panel data estimates of interdependent preferences* by Jose Maria Casado, Francisco Alvarez-Cuadrado, Jose Maria Labeaga and Dhanoos Sutthiphisal
2012-55 *The impact of Medium-Skilled immigration: A general equilibrium approach* by Joan Muysken, Ehsan Vallizadeh and Thomas Ziesemer
2012-56 *Tax incentives or subsidies for R&D?* by Isabel Busom, Beatriz Corchuelo and Ester Martinez Ros
2012-57 *The impact of development aid on education and health: Survey and new evidence from dynamic models* by Thomas Ziesemer