Aid and Human Capital Formation: Some Evidence[1]

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Abstract

This paper uses panel data from a large number of developing countries, two measures of external aid, and a Dynamic Panel Data (DPD) estimator to investigate whether external aid has a significant effect on human capital formation in Less Developed Countries (LDCs). Specifically, we investigate whether external aid targeted to education or the health sector increases primary school enrollment and completion rates and whether aid to the health sector decreases child mortality rates. We find that aid has a significantly positive effect on primary school enrollment and completion rates. Similarly, aid to the health sector significantly decreases child mortality rates in LDCs. We find that aid to the primary education and health sectors are different from the effects of aggregate aid on outcomes in these sectors. We find no evidence of the fungibility of aid to primary education and health sectors in our sample.

KEY WORDS: AID, EDUCATION, HEALTH, LESS DEVELOPED COUNTRIES, DPD ESTIMATOR, POLICY IMPACTS

JEL: O, O1, O53, O54, O55, F35, F43

1 Introduction

This paper uses panel data from a large number of developing countries over the 1990-2004 period to investigate the effects of external aid on human capital formation in Less Developed Countries (LDCs). Specifically, we investigate the effects of aid to the primary education and health sectors on improving outcomes in these sectors in recipient countries. We do so by estimating education and health outcomes equation with external aid to these sectors as additional regressors. We isolate the effects of aid to these sectors on outcomes from those of domestic expenditures and other variables in investigating the aid effects of education and health outcomes. In addition to aid targeted specifically to these sectors, we include several covariates, including policy environment, that affect outcomes in these sectors. In our estimation, we allow for the possibility that some regressors, including aid to these sectors, are endogenous and therefore use an estimator that can account for endogeniety to produce consistent estimates.

The effectiveness of aid in inducing rapid economic growth as a means to reduce poverty in the developing world is a highly debatable topic in the development economics literature. While some studies find that aid has a positive effect on income growth and poverty alleviation, others find that aid has no significant growth effect hence poverty alleviation. Still other studies find that aid is only effective if it is conditioned on "good" policies in recepient countries. Although aggregate aid may not have a significant positive effect of income growth, it is possible that it may lead to poverty reduction and improvement in the living standards of many people through improved health, education, and reductions in hunger.

It is possible for targeted aid to have the intended effect without having growth effect, at least in the short run, for several reasons. First, it is possible for aid to a particular sector (e.g. education) to have the intended outcome (increased enrollment, graduation rates), but this may not translate into increased economic growth because of intermediating factors. Second, it is possible for aid to a sector to be accompanied by reductions in domestic resource allocations to that sector or a reduction in domestric resource mobilization even though domestic resource allocation to that sector does not change. However, recent studies suggest that although aid may be fungible, the flypaper effect operates for aid targeted to specific sectors in developing countries (van de Walle and Mu :2007). Third, it is possible for aid to lead to income growth but will not have any effect on poverty alleviation if growth is not poverty reduction focused. Finally, it is possible for aid to contribute to growth in sectors that receive aid but sectors that do not receive aid may have negative growth, thus counteracting the growth effect of aid.

The developed world has promised massive infusion of aid to the developing world in order to achieve the Millennium Development Goals (MDGs).[1] Education and health are two of the cornerstones of development enshrined in the MDGs hence even if aggregate aid does not have any significant growth effect in developing countries, aid may contribute to the achievement of the MDGs if it significantly improves education and health in these countries. Though much work has been done on the growt effect aggregate aid, very little work has been done on the effectiveness of aid to specific sectors. Given the controversies surrounding aid effectiveness at the aggregate level, and the promise of increased aid, it is necessary to establish the effectiveness of aid to the sectors for which they are intended. This paper is intended to contribute to the literature in this direction.

We focus on education and health for a couple of reasons. Apart from being important inputs in the income growth process (human capital) as well as being two of the important components of the MDGs, they are important aspects of human well being, unlike income which is a means to attaining this well being. In addition, donors have in recent years, targeted these sectors to receive increased aid. As important as education and health are in the welfare functions of all people and mostly those in LDCs, very little attention has been paid to the effects of aid to these sectors.

This paper makes several contributions to the literature: This is one of the few studies that focus specifically on the effects of aid to two important elements of development—education and health—rather than on the effectiveness of aggregate aid on income growth. Second, we use two measures of aid to the sector—as a ratio to GDP and as per capita aid. Third, we control for a large number of regressors as well as test for the importance of the policy environment in the effectiveness of aid to the specific sector. Fourth, we compare the effect of aid specifically to the health and primary education sectors to those of aggregate aid on outcomes in these sectors. Finally, our study uses panel data from a large number of developing countries as well as employ a dynamic panel estimator that accounts for the endogeniety of several regressors.

Our results can be summarized as follows: We find that aid to education and health sectors have statistically significant positive effects on school enrollment and significant reductions in infant mortality rates in developing countries after we control for a large number of explanatory variables. The results are robust to the measurement of aid. We find that the policy environment is important for the effectiveness of health and education aid. We also find regional differences in enrollment and mortality rates in our sample. Finally, we find that while aid targeted to health and primary education sectors have significant impact on outomes in these sectors, general aid has no significant impact on outcomes in these sectors. Our results have implications for aid policy as well as for research on the debate over aid effectiveness.

The rest of the paper is organized as follows: Section 2 reviews the literature and briefly describes the growth equation we estimate, section 3 describes the data and estimation method we use in this study while section 4 presents and discusses the statistical results. Section 5 concludes the paper.

2 Previous Studies and Model

2.1 Previous Studies

The major focus of the large and growing literature on aid effectiveness in the last decade and half has been on aggregate growth and whether the ability of aid to have a positive impact on growth is conditioned on "good" policies. While some researchers find a positive significant growth effect of aid (e.g. Hansen and Dalgaard: 2001), others find that aid has no significant growth effect (e.g. Boone: 1996, Easterly: 2003); still others find that aid has growth effects only if it is conditioned on "good" policies. Of course it is possible for aid to have an effect on some aspect of human development (e.g. education, health) without having any significant impact on income growth. Because of this, some researchers (Gormanee *et al*: 2005, Gormanee, Girma, and Morrissey: 2995, Mosley *et al*: 2004, Verschoor and Kalwij: 2006) have called for the disaggregation of aid effectiveness studies to the sectoral level. Surprisingly, very little work has been done on how aid affects development in specific sectors of LDCs (e.g. health, education, agriculture). In particular, there have been relatively few studies on the effects of aid on the one hand and education and health on the other.

Dreher, Nunnenkamp and Thiele (2006) use panel data and a dynamic panel estimator to investigate the effects of aid to education on educational attainment in LDCs. Using primary school enrollment as the measure of education outcome, they find that aid has a robust and statistically significant positive effect on primary school enrollment rates. They find that institutional quality has no robust effect on educational outcome or the effectiveness aid in their sample. Michaelova and Weber (2006) use panel data and a dynamic panel data estimator to investigate the effects of aid on education. Measuring education outcome as both primary school enrollment and graduation rates, they find a small positive and statistically significant effect of aid on primary school enrollment and completion rates. They conclude that these effects are too small to matter very much economically. The paper finds that policies and institutions in recepient countries matter enormously for the effectiveness of aid on education.

There are even fewer empirical studies done on the effects of aid to the health sector on health outcomes in LDCs. The few studies that have been conducted in this area fall into two categories—those that look at the effects aid to the health sector on health outcomes and those that look at the effects of aggregate aid on health outcomes. Mishra and Newhouse (2007) uses panel data to investigate the effects of aid on several measures of health outcomes. They find that total aid per capita and per capita health aid significantly *reduce* infant mortality rates but do not have statistically significant effect on life expectancy. The paper finds that aid to the health sector stimulate additional spending on health in recepient countries and this may partly account for the effectiveness of health aid in improving health in recepient countries. Their results are robust to several specifications and estimation methods.

Gomanee *et al* (2005) finds that aggregate aid improve Human Development Index (HDI) and reduces infant mortality in in LDCs. This result is robust to specifications that adjusts for whether aid is pro-poor or not. Similarly, Gomanee, Girma, and Morrisey (2005), using quantile regressions analysis, find that aggregate aid improves human welfare and decreases infant mortality. The benefits of aid on health and human welfare are higher at the lowest income levels. Verschoor and Kalwij (2006) find that aid increases recepient governments expenditure on social spending and increases the absolute *income elasticity* of poverty and infant mortality reduction in the recepient countries. Boone (1996) finds that aggregate aid has no significant impact on infant mortality or income growth in LDCs.

While very little work has been done on the effects of aid to the health or the education sector on health and education outcomes, there have been several studies that investigate the effects of government spending on education and health on outcomes in these sectors. A few studies also investigate the effects of aggregate (sectoral) aid on public expenditure on education and health.

Although not directly to the study of the effectiveness of aid to the education and health sectors, Gupta *et al* (1999) find that public expenditures on health and education lead to reductions in infant mortality and increased school enrollment rate in LDCs. They also find that the increased school enrollment persists through the 4th grade. Baldacci *et al* (2004) finds that expenditure on education is the only significant determinant of primary school enrollment. The paper does not, however, distinguish between domestic resources and aid to these sectors. Filmer and Pritchitt (1999) and Roberts (2003) on the other hand find that expenditure on education has no significant effect on enrollment rates once one adjusts for income.

2.2 Model

There are several possible reasons why aid to the education and health sectors can have a significant positive impacts on school and education outcomes in LDCs. In the simplest form, external aid may add to domestic resources to that sector in the absence of aid fungibility. Unless the marginal productivity of additional resources to the health or education sectors are zero or less, the additional resources are likely to add to increased outcomes in these sectors.[2] Second, aid could allow these sectors to import complementary inputs that enhance the productivity of existing resources. For example, aid to the education sector could allow countries to import books and other supplies that will allow teachers to be more productive. In the same way, aid to the health sector could allow the sector to import medicines and equipment to increase the productivity and outcomes in the health sector. Third, aid could lead to increased domestic resource allocation to that sector, especially if this aid is aid has co-funding requirement. Fourth, aid could lead to sectoral reforms that lead to efficiency, especially if aid is conditioned on such reforms. Finally, aid may improve the general environment for policy, hence increase efficiency over all in that sector.

We follow the papers of Dreher *et al* and Michaelowa and Weber (2006) as well as those of other researchers (Gupta *et al*: 1999, Bhalotra: 2007a,b, Mishra and Newhouse: 2007, among others) and propose a simple model of education (health) outcome function in which aid to the sector is an additional explanatory variable in the outcomes equation. We estimate reduced form equations for education and health sectors. The general form of this equation is given as:[3]

$$y_{it} = \alpha_0 + \alpha_1 aid_{it} + \mathbf{X}\beta + \gamma_i policy_{it} + \epsilon_i + \delta_t + \varepsilon_{it} \tag{1}$$

where y_{it} is outcome in the education or health sector, *aid* is aid to the education or health sector, $\mathbf{X}$ is a vector of regressors that influence education (health) outcome in a country, *policy* is the policy environment in a country, α, β, and γ are coefficients to be estimated, ϵ_i, δ_t and ε_{it} are country specific, temporal, and idiosyncratic error terms respectively.

Variables contained in the **X** vector are variables that have been used in the literature to explain educational (health) outcomes at the aggregate level. We note that not all elements, or for that matter the same elements of **X**, will enter both the education and health outcomes equations. For the education equation, these variables include per capita income, expenditure on education net of external aid to education, adult literacy rates and pupil/teacher ratio. These are the variables that have been used by earlier researchers to investigate the determinants of educational outcomes (e.g. Filmer and Pritchitt: 1999, Baldacci *et al*: 2004, Michaelowa and Weber: 2006, Dreher *et al*: 2006). For the health outcome equation, the variables in the **X** vector include lagged health outcome, per capita income, adult literacy rate, health expenditure net of aid, the growth of income, and population growth rate (Bhalotra: 2007a, Mishra and Newhouse: 2007, Gormanee *et al*: 2005, Cutler and Llera-Muney: 2006). In addition to these variables, we also include a variable to represent the policy environment.

We expect the coefficient of income, literacy rates, and expenditure in these sectors net of aid to be positive, all things equal. There is a disagreement in the literature on the effects of aid on health and educational outcomes. While some researchers argue that aid leads to increased outcomes in these sectors, others argue that aid does not have any effect on these outcomes on account of the fungibility of aid. We therefore cannot sign the coefficient on aid to these sectors *a priori.* We leave the sign of *aid* as an empirical issue.

3 Data and Estimation Method

3.1 Data

The dependent variables in the equations we estimate are education and health outcomes. We proxy education outcome as the primary school completion rate (*primarycomp*) in a country. While education outcome should be measured in terms of completion rates and some measure of educational quality, we do not have data on the *quality* of primary school graduates. We therefore measure the *quantity* dimension of educational attainment. We measure health outcome as the infant mortality rate per 1000 births (*infantmort*) in a country. Infant mortality rate is more likely to respond to aid much more than other measures such as life expectancy at birth or morbidity rates for which there is very little reliable data in developing countries. Data for *primarycomp* and *infantmort* were obtained from the World Bank's *World Dvelopment Indicators, 2006.*

The variables of interest in this paper are the external aid to education (*educaid*) and aid to the health sector (*healthaid*). We measure both *educaid* and *healthaid* in two ways—as net aid sibursement to these sectors as a percentage of GDP (*aidprizgdp, healthaidgdp*) and as aid per capita (*aidpricap, healthaidpercap*). Both ways of measuring aid to the education and health sectors adjust for differences in country (economy) size. The control variables in the model are adult education (*adultlit*), per capita income and its growth rate (*gdpcap, gdpcapgrow*), policy environment, population growth rate (*popgrow*), and pupil/teacher ratio (*pupteachrat*) as a proxy for the quality of instruction in primary schools. Other control variables are the expenditure on primary education net of foreign aid to primary education (*primaryexp*), and health care expenditure net of foreign aid to the health sector (*healthexp*).

We measure adult education as the average years of education attained by the adult population (25 years and above) (*adultlit*), income is as the per capita real income (*gdpcap*) measured in 2000 PPP of a country in a year, while income growth (*gdpcapgrow*) is measured as the annual growth rate of real per capita GDP. Health expenditure (*healthexp*) is measured as the ratio of total health expenditure net of health aid to GDP.[4] We measure *primaryexp* as the ratio of net expenditure on primary education to (of foreign aid to primary education) GDP while *adultlit* is measured as the educational attainment of population that is 25 years or older. Similar to *primaryexp*, we measure *healthexp* as the ratio of net expenditure on health to GDP ratio.

The data on education and health aid disbursement are from the 5-CRS/Aid Activities-Disbursements database, which is part of the OECD Development Assistance Committee (DAC) Credit Reporting System (CRS). The database has comprehensive information on education projects in developing countries funded by DAC member countries. The data includes information such as the names of the donor and recipient countries, name of the agency implementing the project (includes non-governmental agencies and other agencies such as UNICEF, EC), a description of the project (teacher training, equipment), starting and ending dates of the project, the level of education being funded (primary, secondary or higher), the type of aid (grants or loans), the amount committed by the donor, the year of commitment and the amount of funds disbursed each year. The data are available from 1990-2004. Similar details are presented for the health aid as well in the CRS. Based on the data, we constructed our variable of interest, which is the amount of aid disbursed to each recipient country every year for education or health.

We point out two caveats of the aid data. First, the years of coverage is short—the data is available for only 15 years. Second, the data does not capture all the education aid flows to the various recipient countries—the database does not have data on aid from non-DAC countries and important multilateral agencies such as the World Bank. We however note that aid from DAC countries constitute over 85% of official assistance to developing countries. For example, the breakdown of the gross official aid to developing countries in 2004 was 89.7 percent for DAC countries, 8.7 percent for multilateral agencies and 1.6 percent for non-DAC countries (OECD, 2006). We therefore feel that the DAC data captures the largest part of education and health aid to developing countries.

Eegarding the control variables, the measure of institutional quality reflects the impartiality of the legal system and the extent to which the rule of law is enforced (*lawandorder*). The variable ranges from 0 to 6, a higher rating implies a more impartial legal system. The data are from the International Country Risk Guide, published by Political Risk Services. The remaining variables—GDP per capita, the growth rate of GDP per capita, population growth rate, expenditure on primary education, pupil/teacher ratio, adult literacy rate, and health expenditure are obtained from the *World Development Indicators, 2005* CD-Rom, published by the World Bank. The analysis covers 90 developing countries; 56 of which are classified as middle income countries and 34 low income countries over the period 1990-2004.[5] To reduce the noise in the annual data, we follow the practice in the literature and average the data over three years.[6] The years of coverage and the countries included in the analysis are determined by the availability of data. We do not have complete data for all years for all years for all countries in the sample hence our data is an unbalanced sample of 392 observations.

Summary Statistics of the sample data are presented in table 1. The average growth rate of per capita income in the sample during the sample period 1.4%, a figure that is relatively high but highly variable. While the mean per capita GDP is about 4500, the standard error of income is about 4900, suggesting a wide variance in per capita income in the sample.[7] Net aid flows to the primary education and health in the sample is relatively high but with large standard errors. The large standard error of aid to the health and primary education sectors relative to their means suggest that some countries in the sample experienced net outflow of "aid" to these sectors. An interesting aspect of the sample date is that the sample mean of *lawandorder* is relatively low, suggesting that these countries, on average had poor policy environments.

3.2 Estimation Method

The growth and investment equations we estimate have endogenous regressors (investment, gdpcapgro, aidgni, among others) as well as country heterogeneity. It is well known that in such cases, the fixed effect (FE) and the random effects (RE) estimators are not consistent. Under these circumstances, researchers have either used an instrumental variable (IV) or general method of moments (GMM) estimators to consistently estimate the growth equations. A consistent estimator that has recently been used by researchers to estimate cross-country growth regressions in a panel format is Arellano and Bond's Dynamic Panel Data (DPD) estimator (Arellano and Bond: 1991). This estimator is a GMM estimator that uses lagged levels of endogenous and predetermined regressors as instruments in a difference equation.

Arellano and Bond proposed a one-step and two-step estimators—with the two step estimator being the optimal estimator. The difference between the two estimators is the weighting matrix. The one-step estimator is obtained when the weighting matrix is the average covariance matrix of $Z\bar{v}_i$ given by $A_N = (N^{-1}\sum_i Z_i' H Z_i)^{-1}$ where H is a $T-2$ square matrix with 2s in the main diagonal, -1s in the first sub-diagonal, and 0s everywhere else. The optimal two step estimator replaces the H matrix with an estimated variance-covariance matrix formed from the residuals of a preliminary consistent estimate of θ. The optimal choice of A_N for the two step estimator is given as: $A_N = \hat{V_N} = N^{-1}\sum_i Z_i'\hat{\bar{v}}_i\hat{\bar{v}}_i Z_i$ where $\hat{v}_i$ are the residuals obtained from a preliminary consistent estimate of θ. The two estimators will be asymptotically equivalent if the error terms are spherical. There is no reason to believe that the error terms are spherical, hence We use Arellano and Bond's two-step estimator to estimate the equations in this study.

The DPD estimator consistently estimates dynamic panel data equations and has been used in several recent panel data studies (Burnside and Dollar: 2000, Easterly *et al*: 2004, Roodman: 2000, among others). However when the series are persistent, lagged levels of endogenous and predetermined regressors tend to be weakly correlated to their subsequent first differences, thus leading to biased estimates on account of weak instruments. Blundell and Bond (1998) have introduced the "systems DPD" estimator to correct this problem. The "systems estimator" adds a levels equation with lagged values of first differences of endogenous and predetermined regressors as instruments to the difference equation and jointly estimate the two equations as a system. We use the systems estimator to estimate both the growth and investment equations. In our estimation, we base all statistical tests on small sample statistics, hence we base our overidentifying restriction test on Hansen's statistivs. We use the systems estimator to estimate the equations in this study. For the purposes of comparison, we also present fixed effects estimates of each equation.

In the presence of regressors that are correlated with the error terms, the FE estimator produce inconsistent estimates while the DPD estimator produces consistent estimates. On the other hand, if all regressors are exogenous, the DPD estimator produces consistent but inefficient estimates while the FE estimator produces both consistent and efficient estimates. We therefore use a Hausman test to test for the exogeneity of regressors. We also test for the presence of second order serial correlation since the validity of the DPD estimates depend crucially on the absence of autocorrelated errors.

4 Results

The results are presented in Tables 2 and 3. Table 2 presents the estimates of the primary school competion rate equation while table 3 presents the estimates for the infant mortality rate equation. In both tables, column 2 presents a fixed effects equation to be compared with the DPD estimates in the other columns.

4.1 Education

Estimates of the primary school completion rate are presented in table 2. Columns 3 and 4 present the DPD results with *aidprizgdp* as the measure of aid while column 5 presents the estimates of the equation that uses *aidpricap* as the measure of aid. In general, the regression statistics suggest that the equation fits the data reasonably well. In particular, the F statistics lead to a rejection of the null hypothesis that all slope coefficients are jointly equal to zero at any reasonably confidence level; there is no evidence of second order serial correlation, the Hansen test passes the over-identifying restriction test and this leads to conclude that the model is properly specified and the instrument vector is appropriate. The Hausman statistics leads us to reject the null hypothesis that the FE is the appropriate estimator for this equation; it suggest that the DPD estimator is the appropriate estimator for the primary school completion rate equation.

Column 2 presents the FE estimates of the primary school completion rates equation. Generally the model fits the data reasonably well as indicated by the regression statistics. Some of the estimated coefficients have the expected signs but are mostly insignificant in the statistical sense.

The coefficient of *gdpcap* and *primaryexp* are positive but statistically insignificant at any reasonable confidence level. This suggests that primary school enrollment is not significantly related to income levels and expenditure on primary education. The coefficients of *pupilteachrat*, *adulutlit*, and *time* are negative but statistically insignificant at $\alpha = .10$. The coefficient of *lawandorder* is positive but statistically insignificant.

The coefficient of *aidprizgdp* is positive but statistically insignificant at any significant level, suggesting that all things equal, an increase in primary education aid/GDP ratio is not significsntly correlated with increases in primary school completion ratios in LDCs. The FE estimates suggest that aid, per capita GDP, and other regressors have no significant effect on primary school enrollment ratios in LCDS. Some of the coefficients have the unexpected signs and the fact that the Hausman test shows that all regressors in the primary school enrolment ratio equation are not exogenous suggests that the FE estimator is not appropriate for this equation. We will therefore focus our discussions on the DPD estimates in columns 3–5.

Column 3 presents the DPD estimates of the primary school completion rate equation. The coefficients of *gdpcap* and *adultlit* are positive and significantly different from zero at $\alpha = .01$ or better. These estimates suggest that primary school completion rate is positively related to the levels of per capita income and adult educational attainment, all things equal. The coefficient of *lawandorder* is positive and significantly different from zero at $\alpha = .05$ suggesting that the policy environment has a significant effect on primary school completion rates, all things equal. Countries that have "good" index of governance have higher rates of primary school completion rates in LDCs, conditional on other regressors. This is consistent with the results of research that find the policy environment as an important determinant of economic development.

The coefficient of *primaryexp* is positive and statistically significant, indicating that there is a positive correlation between primary school expenditure and primary school completion rates in LDCs, all things equal. The coefficient of *pupilteacherat* is negative and significant at $\alpha = .05$, suggesting that there is a negative relationship between the quality of schools as measured by pupil/teacher ratios and enrollment rates, all things equal. The coefficient estimates of the regional dummies suggest that there are significantly large regional differences in primary school completion rates in the sample.

What is the effect of primary school aid on primary school completion rates? The coefficient of *aidprizgdp* is positive, relatively large, and significantly different from zero at $\alpha = .01$ or better.

This suggests that aid to the primary education sector is positively correlated with primary school completion rate in LDCs, all things equal. The fact that we control for several factors that are likely to affect primary school completion rates suggests that this estimate is not due to some omitted variable bias and suggest that external aid to the primary education sector increases primary school enrollment rates in recepient countries. This positive coefficient estimate is *qualitatively* similar to the results obtained by other researchers (Michaelowa and Weber: 2006, Baldacci *et al*: 2006, Gupta *et al*: 1999, among others) although our results are *quantitatively* much larger.[7]

Gomanee, Girma, and Morrissey (2005) conclude that aid improves the welfare of those at the bottom of the income distribution more than those at the top. If this were to carry to the regional level, aid to primary education and health will have more impact on outcomes in Sub-Saharan African countries—the poorest region in the developing world—than other parts of the world. In column 4, we add the interaction between *ssa* and *aidprzgdp* to see if the completion effect of primary school aid differs for Sub-Saharan African countries compared to other regions of the world. All the estimates in column 4 are similar in sign, magnitude, and statistical significance as their counterparts in column 3. In particular, the coefficient *aidprzgdp* is positive, larger than unity, and significantly different from zero at $\alpha = .01$, confirming the results in column 3. The coefficient *ssa.aidprizgdp* is negative, relatively small but statistically significant at $\alpha = .01$ or better. This indicates that aid to primary education increases primary school completion rates in Sub-Saharan Africa by less than it does in other parts of the developing world. This conclusion is different from the results of Gormanee, Girma and Morrissey (2005) who find that aid is more effective an reducing poverty at lower levels of income than at higher levels of income, all things equal.

Our results in columns 2-4 are based on measuring education aid as the primary education aid/GDP ratio. It is possible that our results are driven by this measure of aid to primary education. We use an alternative measure of aid to primary education—aid to primary education per capita—to investigate the effects of aid on primary school enrollment rates as a robustness check on our results. The estimates are presented in column 5. All coefficient estimates are similar in sign and statistical significance to their counterparts in columns 3-4. The coefficient of *educaidpercapita* is positive and statistically significant at $\alpha = .01$, indicating that per capita aid to education has a strong positive impact on primary school completion rates, all things equal. This suggests that increases in per capita aid to primary education is significantly associated with increases in primary school completion rate. The positive significant coefficient on *educaidpercap* and the fact that the coefficients of other variables are not affected in column 5 suggests that our result that aid to primary education increases primary school completion rate is not dependent on how we measure aid to primary education.

4.2 Health

The estimates of the infant mortality rate equation are presented in table 3. Columns 3 and 4 present the DPD estimates of the equation when health aid is measured as *healthaidgdp* while columns 5 and 6 present the estimates in which health aid is measured as health aid per capita (*healthaidpecap*). Column 2 presents FE estimates of the equation for the purposes of comparison. In general, the regression statistics indicate that the model fits that data reasonably well and most of the coefficient estimates are of the expected signs. In particular, the F statistics leads us to reject the null hypothesis that all slope coefficient are jointly equal to zero; there is no evidence of second order serial correlation and the Hansen test statistic suggest that the instrument vector used to estimate these equations are appropriate. Finally, the Hausman statistic suggest that the DPD estimator, rather than the FE, is appropriate for this equation.

The coefficient estimate of *gdpcap* and *healthexp* in column 2 are negative and significantly different from zero at $\alpha = .01$ or better, all things equal. The coefficients of *adultlit*, *popgrow*, *lag.mortrate*, *lawandorder*, and *gdpcapgrow* are positive and significantly different from zero at $\alpha = .05$ or better. The estimate of the coefficient of *adultlit* suggests that infant mortality rate increases with literacy rates, a result that is counter-intuitive (Cutler and Lleras-Muney: 2006, Gyimah-Brempong and Wilson: 2004, Mishra and Newhouse: 2007, and Roberts: 2003, among others). The coefficient of *popgrow* is unreasonably large at about 3. The coefficient of *time* is negative, relatively large, but statistically insignificant.

The coefficient of *healthaidgdp* is negative and significantly different from zero at $\alpha = .05$ suggesting that health aid leads to reductions in infant mortality rates in LDCs, all things equal. This estimate is consistent with our expectations. However, the unexpected positive coefficient of *adultlit*, the very large coefficient of *popgrow* and *time* cast some doubts on the validity of the FE results. More important, the Hausman test statistics in columns 3-6 lead to a rejection of the null hypothesis that all regressors in the infant mortality equation are exogenous. Given these, it appears that the FE estimates are biased, hence we will focus our discussions on the DPD estimates.

In column 3, the coefficients of *gdpcap* and *adultlit* are negative and significantly different from zero at $\alpha = 0.01$ or better. This suggests a strong negative relationship between income levels and adult literacy rates on the one hand and infant mortality rate on the other; a result that is consistent with our expectation and the literature generally. The coefficient of the growth rate of per capita GDP (*gdpcapgrow*) is positive and significant at $\alpha = 0.01$ or better, suggesting that there is a positive relationship between economic growth rate and infant mortality in our sample. This result seems counterintuitive and inconsistent with Ghalotra's (2007a) results. The coefficient of *lag.mortrate* is positive, relatively large, and significantly different from zero at $\alpha = .01$ or better. The coefficient estimate of *lag.mortrate* suggests that mortality rates in the current period is positively related to mortality rate in the previous period with a relatively slow rate of adjustment. The coefficient of *lawandorder* is negative and significantly different from zero at $\alpha = .05$ or better indicating that countries with better policy environments have lower infant mortality rates, all things equal.

The coefficient of population growth rate *popgrow* is positive, very large, and significant at $\alpha = .01$, suggesting that high population growth rate is associated with high infant mortality rates, all things equal. The coefficient of health expenditure (*healthexp*) is negative and significantly different from zero at $\alpha = .05$, all things equal. This suggests that health expenditures other than aid have significant impact on infant mortality rates in the sample countries; specifically, increases in health care expenditures results in decreases in child mortality in developing countries, all things equal. The estimates also suggest that there are regional differences in infant mortality rates showing statistically higher rates in Sub-Saharan Africa, Middle East and North Africa, South Asia, but insignificant lower rates in Latin America and East Asia and the Pacific. The coefficient of *time* is negative and statistically significant at $\alpha = .01$ suggesting that infant mortality rates decreased over time during the sample period in LDCs.

What is the effect of health aid on infant mortality rates in our sample of LDCs? The coefficient of *healthaidgdp* is negative, relatively large, and significantly different from zero at $\alpha = .01$ or better. The coefficient estimate suggest that a percentage point increase in the health aid/GDP ratio is associated with 0.34 points decrease in infant mortality rates, all things equal. The coefficient estimate suggests that health aid has a relatively large and significant effect on the reduction of infant mortality rates in LDCs after controlling for a large number of regressors, including domestic expenditures on health. It may suggest that the health aid impact on child mortality is not due to the effects of omitted variables. This result is consistent with the results obtained by Gormanee *et al* (2005), Mishra nd Newhouse (2007), Roberts (2003), and Verschoor and Kalwij (2006).

In column 4, we add the interaction of health aid and Africa dummy variable (*afr.healthaidgdp*) as an additional regressors on the account that health aid is likely to have a higher impact in low income countries (Gomanee, Girma, and Morrissey: 2005) than in higher income countries. The coefficient estimates of all variables remain unchanged compared to their counterparts in column 3. In particular, the coefficients of *gdpcap*, *adultlitrate*, *lag.mortrate*, *gdpcapgrow*, *popgrow*, and *time* remain unchanged and continue to be statistically significant at $\alpha = .05$ or better. The coefficient of *healthexp* is negative and significant as in column 3 signifying that health expenditures have negative and significant effects on child mortality in LDCs, all things equal.

The coefficient of *healthaidgdp* in column 4 is negative and significant, suggesting that health aid has significantly negative impacts on infant mortality rates in LDCs after adjusting for other variables that affect child mortality. The coefficient of *afr.healthaidgdp* is negative and significantly different from zero at $\alpha = .05$. We note however that including *afr.healthaidgdp* in the infant mortality rate equation reduces the absolute magnitude of the coefficient estimate of *healthaidgdp*. The coefficient estimates of *healthaidgdp* and *afr.healthaidgdp* indicate that health aid has a larger effect on child mortality rates in African countries relative to its effect in other LDCs, all things equal. This result is consistent with those of Gormanee, Girma, and Morrissey (2005).

The results in columns 2-4 are based on measuring health aid as the ratio of health aid to GDP of a country. Are our results dependent on our measurement of health aid? In columns 5 and 6, we present estimates from an equation that measures health aid as health aid per capita (*healthaidpercap*). As in columns 3 and 4, the coefficients of *gdpcap*, *adultlit*, *healthexp*, and *time* are negative and significantly different from zero at $\alpha = .05$ or better while those of *lag.mortrate*, *gdpcapgrow*, and *popgrow* are positive and significant. The estimates also show regional differences in infant mortality rates with the order of regional effects very similar to those in columns 2-4.

The coefficient of *healthaidpercap* in columns 5 and 6 is negative, relatively large and significantly different from zero at $\alpha = 05$ or better, indicating that all things equal health aid per capita is associated with reduction in infant mortality rates in the sample. Similar to the estimates in columns 3 and 4, the coefficient of *afr.healthaidgdp* in columns 5 and 6 is negative and significant at $\alpha = .05$ indicating that health aid per capita has a larger effect on infant mortality rates in Africa relative to its effect in other parts of the developing world. The estimates in columns 5 and

6 indicate that the effects of health aid on child mortality rates in our sample is not dependent on how we measure health aid.

Our results are consistent with those of Michaelowa and Weber (2006), Dreher, Nunnemkamp, and Theile (2006), Gomanee, Girma, and Morrissey (2005), Gomanee, Morrissey, Mosley, and Verschoor (2005), and Mishra and Newhouse (2007) who find that aid to education and health sectors have positive and significant impact on outcomes in these sectors. However, while Dreher *et al* (2006) find that the policy environment does not matter for primary school outcomes, we find that the policy environment matters for both primary school and health outcomes. The results are also consistent with the results of studies that find that increased public expenditures on education and health in LDCs improve outcomes in these sectors (Gupta, Verhoeven, and Tiogson: 1999, Wolfe: 2006). The results suggest that the proposed increased aid to LDCs, if properly targeted, could help in reducing poverty and improve the living stards of many people and brighten the prospects for long term development in the developing world.

4.3 Effects of Aggregate Aid on Education and Health Outcomes

An argument put forth to explain empirical results that indicates that aid has no significant effect on economic outcomes in LDCs is one of *excessive aggregation* of the aid measure used in such studies. Would our results be different if we had used aggregate aid instead of aid to education and health sectors? We investigate this question by replacing aid to primary education and to the health sector by aggregate aid to the economy measured as total net aid inflow/GDP ratio (*aidgdp*) and total aid per capita (*(* aidpercap) respectively. We find no significant relationship between aggregate aid to the economy and either primary school completion rates or infant mortality.[9] For the primary school completion rates equation, the coefficient estimates for total aid/GDP ratio and total aid per capita are -0.0239 and 0.0002 respectively. None of these coefficients is statistically significant at any reasonable confidence level (the absolute z scores are 0.68 and 0.77 respectively). For the infant mortality rate equation, the coefficient estimates on total aid/GDP ratio and total aid per capita are -0.0612 and -0.0072 with absolute z statistics of 0.12 and 0.26 respectively.

The estimates in this sub-section suggest that aggregate aid has no significant effect on primary school completion rates or infant mortality. This result is consistent with the results of studies that find that aid is not effective in improving economic outcomes in LDCs, all things equal. The insignificant effects of aggregate aid on primary education and health outcomes we find combined with the significant effects of aid to these sectors on the health and education outcomes is consistent with the idea that one of the reasons researchers find no significant aid effects in developing countries is excessive aggregation. Our results argue for disaggregation when investigating aid effectiveness in LDCs.

4.4 Domestic Resources and Aid

Some researchers argue that aid substitutes for domestic resources while others find that aid leads to increased domestic resources to the education and health sectors. Some researchers argue that the observed ineffectiveness of aid is due the fungibility of aid. For example, Boone (1996) partly blames fungibility for aid ineffectiveness in LDCs. On the other hand, Devarajan *et al* (1999) find no evidence of fungibility of aid to education and health in a sample of African countries from the 1970s and 1990s.[10] In the same way, van De Walle and Mu (2007) find little evidence of fungibility of aid to road projects in Vietnam. While this paper is not about the effects of aid on the commitment of domestic resource to the education and health sectors, we nevertheless investigate in a rudimentary way, whether aid substitutes for domestic expenditure on primary education and health. We do so by regressing domestic expenditure on primary education and health on aid to primary education and other control variables, including per capita income, and adult literacy rates. Because we measure expenditure in these sectors as net of aid to these sectors, fungibility will be indicated by a negative and statistically significant coefficient on the aid variables; there will be no evidence of fungibility otherwise.

The results are presented in Table 4. Columns 2 and 3 present the estimates for the primary school expenditure equation while columns 4 and 5 present the estimates for the health expenditure equation.[11] Columns 2 and 4 present estimates for the equations that measure aid as a share of GDP (*aidgdp*) while columns 3 and 5 present the estimates of the equations that measure aid in per capita terms (*aidpercap*). The regression statistics show that the equations fit the data reasonably well and the coefficients are generally of the expected signs. In particular the coefficients of *gdpcap* and *adultlit* are positive and statistically significant at $\alpha = .01$ in all equations, indicating that all things equal expenditure on primary education and health from domestic resources are positively correlated with per capita income and adult literacy rates.

The coefficients of *aidprizgdp* and *eduaidpercap* in columns 2 and 3 are positive but not statistically significant at $\alpha = .10$ or at any reasonable confidence level. The estimates suggest that domestic component of expenditure on primary education is not significantly influenced by the level of external aid to that sector, all things equal. In the same way the coefficient estimates of *healthaidgdp* and *healthaidpercap*, in columns 4 and 5 respectively, are statistically insignificant at any reasonable confidence level. The coefficient estimates of aid to primary education and health suggest that domestic spending in these sectors are not influenced by aid to these sectors. The estimates in this section may suggest that our result that aid to primary education and health sectors in LDCs have positive and significant effects on outcomes in these sectors may be partly due to the lack of fungibility of these resources. Our results are different from those of Veshoor and Kalwij (2006) who find thai aid to social sectors increase public expenditures in these sectors; it is also inconsistent with the results obtained by Boone (1996) wh finds evidence of fungibility of aid in LDCs. It is however, consistent with the results obtained by Gupta *et al* (2003) and van de Walle and Mu (2007).

5 Conclusion

This paper uses panel data from a large number of developing countries over the 1990 to 2004 period and a dynamic panel estimator to investigate the effects of external aid to primary education and the health sectors on outcomes in these sectors. Using infant mortality and primary school completion rates as our measures of outcomes in these sectors, we find that aid has significantly positive effects on outcomes in these sectors. There is evidence of regional differences in the effect aid on outcomes in these sectors. The results are robust to the measurement of aid to these sectors; however we find that aggregate aid is not significantly correlated with outcomes in primary education or health. We also find no evidence that aid to these sectors fungible. Our results are consistent with the results of earlier research that find a significant relationship between sectoral aid and outcomes in these sectors.

Our results have research as well as aid policy implications. Thiele, Nunnenkamp, and Dreher (2006) argue that donors should target their aid, especially to Africa, to the achievement of speccific MDG goals, if poor countries are to achieve the MDGs. They specifically stress education and health as areas where aid could be very effective in achieving the MDGs. Our results support this view. Our results suggest that one way to improve the lives of people through aid is to target aid to the primary education and health sectors. Besides the short to medium benefits, targeting these sectors will lead to increased human capital formation, hence long term development. Targeting aid to the appropriate sectors becomes very important in view of the United Nations and the Commission for Africa's efforts to double aid to Africa and other developing regions in the next decade. Failure to target aid appropriately may lead to the misallocation of aid resources, hence fail to help liberate a large number of people in LDCs from poverty.

From aid research point of view, our results suggest the need for focusing investigating aid effectiveness at the sectoral level rather than the current practice of investigating the growth effect of aggregate aid. Perhaps, redirecting research efforts toward the sectoral effects of aid, looking at which sectors effectively use aid and have better social returns to aid may better help guide aid policy may be a more fruitful avenue than the current approach of focusing on aggregate outcomes.

6 Notes

1. See UNDP (2006) and the Africa Commission Report

2. Although some authors argue that aid substitutes for domestic resources in particular sectors, recent studies suggest that the flypaper effect exists in aid to specific sectors (see for example, van de Walle and Mu: 2007).

3. The equation we estimate is similar to the ones estimates by Dreher *et al* (2006), Gormanee, Girma, and Morrissey (2005), Michaelowa and Weber (2006), and Mishra and Newhouse (2007).

4. This is defined as $(healthexpenditure - healthaid)/GDP$. This makes *healthexp* orthogonal to *healthaid*. We define per capita education expenditure similarly.

5. The countries in the sample are Afghanistan, Argentina, Burundi, Benin, Burkina Faso, Bulgaria, Bangladesh, Bahamas, Belize, Bolivia, Brazil, Botswana, Cambodia, Cape Verde, Central African Republic, Chile, China, Cote d'Ivoire, Cameroon, Colombia, Comoros, Congo, Costa Rica, Dominican Republic, Algeria, Ecuador, Egypt, Fiji, Gabon, Ghana, Guatemala, Guinea, Guyana, Hong Kong, Honduras, Haiti, Indonesia, India, Israel, Jamaica, Jordan, Kenya, Cambodia, South Korea, Lebanon, Ethiopia, Lesotho, Madagascar, Mexico, Malta, Mauritania, Malawi, Malaysia, Mali, Mauritius, Morocco, Mozambique, Namibia, Niger, Nigeria, Nicaragua, Nepal, Oman, Pakistan, Panama, Peru, Philippines, Papua New Guinea, Paraguay, Rwanda, Sudan, Senegal, Singapore, Sierra Leone, South Africa, Slovania, Suriname, Swaziland, Seychelles, Chad, Togo, Thailand, Trinidad and Tobago, Uganda, Uruguay, Tanzania, Venezuela, Vietnam, Zambia, and Zimbabwe. The sample used for this study are dictated by the availability of the requisite data.

6. The usual practice in the literature is to average over five year intervals. Due to the shortness of out time series we would lose most of the observations if we averaged over five years.

7. All nominal values were were converted to 2000 PPP values.

8. We note however, we measure aid to primary education differently from how it is measured by some of these researchers (see for example, Deverjan *et a*: 1999).

9. We do not present the estimates here for space consideration. They are, however, available upon request.

10. We note that our measure of aid to education and health sectors differs from theirs.

11. We do not present the full sets of coefficients, including regional differences in this table.

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Table 1: **Summary Statistics of Sample Data**

Variable	Mean*	Standard Deviation	Minimum	Maximum
healthaidgdp (%)	0.116	0.3748	-0.0012	6.1382
healthexpgdp (%)	6.09	2.09	1.03	62.90
healthaidpercap (PPP_{2000})	5.38	15.87	0.28	213.18
primarycomprate (%)	76.3618	25.45	12.33	121.00
$infantmort$ (per 1000)	52.30	40.43	2.51	191.08
healthexp ($ (PPP_{2000})	6.09	2.09	1.03	62.90
aidgdp (%)	7.81	12.69	-0.14	38.49
prizgdp (%)	0.0432	0.1251	-0.0475	12.3828
primaryexpgdpcap ($)	15.306	7.036	3.47	48.70
primaryaidcap PPP_2000	0.72	3.03	0.00	42.212
gdpcapgr (%)	1.4295	3.8451	-19.4642	25.1583
gdpcap (PPP_{2000})	4842.36	4926.02	453.19	25784.06
adultlit (%)	21.7205	7.9829	0.2105	61.8511
mena	0.1190	0.3240	0.00	1.00
ssa	0.2798	0.4491	0.00	1.00
eap	0.1726	0.3781	0.00	1.00
sa	0.0476	0.2130	0.00	1.00
na	0.0059	0.0769	0.00	1.00
lac	0.2143	0.4106	0.00	1.00
lawandorder	3.441	1.2697	0.1389	6.00
N	392			

* these are unweighted averages.

Table 2: **DPD Estimates of Education Equation**

Variable		**Coefficient**	**Estimates**	
aidprizgdp	0.2030	1.7664***	1.1669**	
	(1.31)	(7.12)	(2.88)	
aidpricap				0.1347***
				(3.28)
gdpcap	0.3031	0.4284***	0.4276***	0.4177***
	(0.51)	(20.78)	(19.14)	(15.93)
primaryexp	0.9912	0.0892**	0.0249**	0.0198**
	(1.08)	(1.89)	(1.79)	(1.86)
pupteachrat	-0.0188	-0.0029**	-0.0189*	-0.0211*
	(1.12)	(2.04)	(1.72)	(1.68)
adultlit	-0.0188	0.0447**	0.0405**	0.0333**
	(1.02)	(2.45)	(1.90)	(2.39)
ssa		0.5998***	0.6068***	0.6395***
		(5.05)	(4.15)	(4.27)
sa		0.9488***	0.9428***	0.9584***
		(7.59)	(7.48)	(6.79)
lac		0.4934***	0.5193***	0.4990***
		(4.39)	(4.47)	(3.82)
mena		0.5474***	0.5359***	0.5060***
		(3.68)	(3.47)	(3.41)
eap		0.6761***	0.5473***	0.5539***
		(5.66)	(3.84)	(3.52)
lawandorder	0.0173	0.0001	0.0128**	0.0369**
	(0.33)	(1.08)	(1.97)	(2.37)
ssa.aidprizgdp			-0.1379***	-0.1164***
			(4.79)	(3.29)
time	-0.0486		0.0109	0.0050
	(0.68)		(1.06)	(0.52)
N	392			
F	28.19	524.93	329.11	308.44
$\mathbf{R}^2$	0.3967			
Between	0.4794			
Within	0.4943			
1st ord. ser. cor.		1.63	2.22	2.31
2nd ord. ser. cor.		-0.24	0.51	0.49
Hansen test		13.96 [11]	14.44 [11]	8.14 [11]
Hausman m		52.98 [9]	57.25 [9]	88.96 [9]

+ absolute value of “t” statistics in parentheses. * 2-tail significance at $\alpha = 0.10$
** 2-tail significance at $\alpha = 0.05$ *** 2 tail significance at $\alpha = 0.01$

Table 3: **DPD Estimates of Infant Mortality Equation**

Variable		**Coefficient**	**Estimates**		
heathaidgdpgdp	-0.0137	-0.3357***	-0.2558**		
	(0.78)	(6.10)	(4.08)		
healthaidpercap				-0.3941**	-0.2659**
				(2.20)	(1.75)
healthexp	0.0784**	-0.0539**	-0.0958***	-0.02249**	-0.2234**
	(2.39)	(2.01)	(3.09)	(2.09)	(1.89)
gdpcap	-0.7619***	-0.0054***	-0.3404***	-0.3892***	-0.3866
	(9.05)	(4.56)	(3.68)	(4.62)	(6.25)
gdpcapgrow	0.0096	0.1220***	0.0289***	0.0423***	0.0479**
	(1.14)	(8.66)	(2.98)	(3.74)	(2.65)
lag.mortrate	1.0596***	0.6602***	0.6082***	0.6063***	0.5438***
	(14.06)	(18.02)	(8.84)	(11.04	(10.30)
popgrow	0.0337**	1.1102***	0.0259**	0.1696***	0.1031***
	(1.77)	(13.18)	(1.80)	(4.78)	(3.14)
lawandorder	-0.0678**	-0.0986***	-0.1028***	-0.1596***	-0.1488***
	(2.39)	(3.89)	(3.09)	(4.06)	(2.96)
time	-0.3658	-0.0512***	-0.0489***	-0.0563***	-0.0727***
	(1.44)	(3.08)	(2.92)	(2.43)	(2.75)
sa		0.5124**	0.4984**	0.4782***	0.4782**
		(2.11)	(2.17)	(3.49)	(2.58)
lac		0.4934**	-0.4821	-0.5932**	-0.4992
		(2.19)	(1.51)	(2.28)	(1.44)
mena		0.9781***	1.0915***	1.487***	1.6885***
		(4.68)	(5.12)	(4.58)	(5.07)
eap		-0.2486	-0.1894	-0.1289	-0.0168
		(1.41)	(0.98)	(1.35)	(1.06)
ssa.aidprizgdp			-0.0189**		-0.0214***
			(1.87)		(3.29)
N	392				
F	196.59	287.89	342.89	690.61	528.26
$\mathbf{R}^2$	0.8598				
Between	0.9596				
Within	0.3152				
1st ord. ser. cor.		-2.84	-3.24	1.02	1.00
2nd ord. ser. cor.		0.44	0.51	-1.04	-0.97
Hansen test		3.55 [12]	7.28 [13]	8.14 [12]	11.21 [13]
Hausman m		52.98 [9]	57.25 [9]	88.96 [9]	79.22 [10]

+ absolute value of "t" statistics in parentheses. * 2-tail significance at $\alpha = 0.10$
** 2-tail significance at $\alpha = 0.05$ *** 2 tail significance at $\alpha = 0.01$

Table 4: **Estimates of Expenditure Equations**

Variable	**Coefficient**		**Estimates**	
	Eduexp		**Healthexp**	
heathaidgdp			-0.5186	
			(0.71)	
healthaidpercap				0.0394
				(1.34)
aidprizgdp	28.5827			
	(1.00)			
eduaidpercap		0.3267		
		(1.35)		
gdpcap	0.0011**	0.0010**	0.0003***	0.0006***
	(2.27)	(1.94)	(2.65)	(9.89)
gdpcapgrow	-0.3634***	-0.3198***		
	(3.34)	(3.41)		
popgrow			0.4425*	0.2608
			(1.60)	(1.00)
adultlitrate	0.2652**	0.2263**	0.2429**	0.1982**
	(2.41)	(1.98)	(2.16)	(1.98)
lawandorder	4.0622***	3.7711***	0.8759***	0.7523***
	3.70)	(3.38)	(4.37)	(3.58)
N	392			
F	86.58	76.29	64.41	55.21
1st ord. ser. cor.	1.86	1.09	1.87	1.08
2nd ord. ser. cor.	0.28	0.28	0.19	0.27
Hansen test	13.28 [11]	11.24 [11]	9.89 [12]	10.88 [13]
Hausman m	68.29 [9]	59.16 [9]	68.11 [8]	59.87 [8]

+ absolute value of "t" statistics in parentheses. * 2-tail significance at $\alpha = 0.10$
** 2-tail significance at $\alpha = 0.05$ *** 2 tail significance at $\alpha = 0.01$