Infrastructure, growth and poverty: some cross country evidence

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1. Introduction

Infrastructure is 'back in fashion' as far as the donor community is concerned with the argument that that meeting the millennium development goals will require heavy infrastructure investment to meet both income poverty and social targets. Current ADB estimates put the infrastructure needs of developing Asia at $300 billion over the next five years (van der Linden 2004). In this paper we address the question of infrastructure's impact both on economic growth and poverty reduction. Our focus is primarily on a comparison across countries, although we test one of our cross-country findings with data from a single country, PRC. We aim to test two simple hypotheses – first that higher infrastructure activity is related positively in a causal sense to economic growth and second that infrastructure has a direct effect on poverty in addition to any indirect effect through higher growth. These are very basic propositions and may seem self-evident to many observers. However proving infrastructure causes economic growth as opposed to responding to it is challenging in terms of econometric methodology because of problems of endogeneity and reverse causation (that is we may know that infrastructure variables rise with growth but we need to demonstrate where the direction of causation lies). Further there is also the issue of how far infrastructure directly and indirectly reduces poverty, for example by bringing the poor into market relationships and raising the returns to their assets, as well as impacting on them through a 'trickle down' process as higher economic activity creates jobs and markets that they can take advantage of. Our cross country results, although they use best-practice techniques for controlling for country differences, are of course inferior to accurate single country analyses. However, we put them forward as a complement to ongoing national work and because such comparisons show how individual country prospects might alter if their infrastructure stock reaches the level of others.

Our methodology involves two separate sets of calculations. First we test for the impact of infrastructure on economic growth across countries and different time periods. We apply the current best-practice technique of Generalized Method of Moments (GMM) to ensure that any positive relationship between infrastructure and growth runs from the former to the latter. We then use predicted growth to explain changes in poverty. We term this a 'trickle down model,' which can be represented as follows

$$G_{ct} = \alpha + \lambda (X_{ct}) + \mu_{1c} + \varepsilon_{1t} \quad (1)$$

$$G^1_{ct} = \alpha + \lambda^1 (Y_{ct}) + \mu_{2c} + \varepsilon_{2t} \quad (2)$$

$$P_{ct} = \alpha + \lambda^2 (G^e) + \lambda^3 (Y_{ct}) + \lambda^4 (Z_{ct}) + \mu_{3c} + \varepsilon_{3t} \quad (3)$$

where G is economic growth, P is a measure of poverty, X is a vector of factors that explain growth, including an infrastructure variable, Y is a vector of instrumental variables (including lagged X factors), G^e is predicted growth from (2), Z is a vector of non-growth factors that affect poverty, μ captures fixed country specific characteristics, ε is an error term, and subscripts c and t refer to country and time periods, respectively.

Equation (1) is estimated using OLS and panel data techniques, however it will give a biased result due to the presence of a lagged dependent variable and as there will be the strong possibility that variables in X will be determined endogenously as growth proceeds. To correct for this we apply the GMM approach using (2). From this we can get an estimate of effect that infrastructure is likely to have on growth. Predicted growth from (2) then can be used to explain changes in a measure of poverty. Infrastructure variables appear in X and Y and therefore cannot be included separately in Z. Support for the hypothesis that infrastructure causes growth requires a positive and significant coefficient for the infrastructure variable in Y. Provided growth has a negative relation with poverty, so the coefficient λ^2 is negative and significant in (3), we can conclude that infrastructure activity is poverty-reducing. The GMM system does not readily generate a long-run elasticity that links infrastructure with poverty.

Our second approach to address the direct impact of infrastructure on poverty employs what we term an 'ad hoc' model. This employs a simpler analysis that can be represented as

$$P_{ct} = \alpha + \beta^1 (G_{ct}) + \beta^2 (Z_{ct}) + \mu_c + \varepsilon \qquad (4)$$

where G is actual growth and Z is a vector of factors that determine poverty in addition to growth, now including an infrastructure variable.

Support for an impact of infrastructure on poverty requires a positive and significant coefficient on the infrastructure variable in Z. Any further indirect effects of infrastructure on poverty through growth will be captured in G. Here interpretation of an elasticity relation between poverty and infrastructure is straightforward. (4) is applied in a simple form with G as actual growth and in a more sophisticated version to take account of endogeneity with instruments for growth (its lagged values and those of key independent variables).

In analyses of the impact of infrastructure at a macro level there is always a problem of how infrastructure is measured. Most possible infrastructure variables are relatively closely correlated so that the inclusion of several in the above equations will give biased results. A common approach, which we adopt here, is to use one variable, in our case length of road per capita, as a proxy for change in infrastructure overall.[1] Poverty can also be measured in different ways. We experiment with various alternatives but report our results based on headcount measures of income poverty.

We find support for both hypotheses. We find an unequivocal positive relation between infrastructure stocks and economic growth that is not due to causation running from growth to infrastructure. The elasticity is relatively high at about 0.04, implying that a 10% increase in infrastructure stocks raises the growth rate by 0.4% annually. We also find evidence of a direct relation between infrastructure and poverty reduction that is in addition to a growth effect. The average direct infrastructure poverty elasticity is relatively high at - 0.35 for the $1 a day headcount measure and –0.53 for the $2 headcount. However this is not an unconditional relation in the sense that it is only significant in the presence of education endowment (as proxied by a measure of school enrolment) and that its absolute value varies directly with education endowment. This provides support for the widely held view that infrastructure as a direct poverty tool will work best when it is part of a package approach.[2] This cross-country result is supported by similar results from national case studies and we confirm it with an analysis of data from PRC. We also illustrate from our regression results that without additional economic growth the changes in infrastructure coverage (even combined with improvements in education) required for major inroads into poverty are large. For India, for example, a 35% increase in the infrastructure measure is required to bring the headcount down by 19%. This is clearly a non-marginal change.

The remainder of the paper is as follows. Section 2 discusses questions of methodology and section 3 discusses the data and the results. Section 4 reports a simple test calculation for PRC. Section 5 concludes.

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[1] The alternative is to use a synthetic or composite measure of infrastructure. This is the approach in Calderon and Serven (2004), who construct a weighted index based on data on telecommunications, power and roads.
[2] See for example the work on 'spatial poverty traps' by Ravallion and Jalan (1999).

2. Methodology:

The theoretical literature on the determinants of poverty does not provide a clear guide as to how to set up a testable empirical model. Recently researchers have applied 'ad hoc' models to establish possible links between poverty and various indicators (for example, Dollar and Kraay (2000), Hanmer and Naschold (2000), Agenor (forthcoming)). Most these models are a reduced form version of the earlier 'trickle down' model of poverty. In all these specifications growth is the key determinant of poverty. The 'trickle down' version can be represented by a system of equations, one for growth and the other for poverty. In the 'ad hoc' models growth appears as an explanatory variable along with others that affect poverty (see equations (1) through (4) above).

Our approach builds on the 'generalised Solow model' (Mankiw et al 1992). Nonneman and Vanhoudt (1996) have extended this approach to include various categories of investment and empirically applied this generalised framework to an evaluation of the effects of three investment categories - physical capital, human capital, and technological know-how -on economic growth. Through a similar framework one can capture the relative magnitude of the impact that infrastructure has on growth. To do this we follow approach of Temple and Johnson (1995) in modifying Mankiw et al. (1992), and argue that total factor productivity (TFP) can be influenced in our case by infrastructure stock (and in their's by social capital).

Temple and Johnson's specification can be summarised as follows

$$\ln y_t - \ln y_0 = \ln A_t + \varphi_1 \ln s_k + \varphi_2 \ln s_h + \varphi_3 \ln(\delta + n + g) + \varphi_4 \ln y_0 \qquad (5)$$

where y is output per unit of labor, subscript 't' stands for the present time and '0' for the initial level. 'A' captures total factor productivity (TFP), 's_k' is the share of investment in physical capital in GDP and 's_h' is the same for human capital, 'δ' stands for capital depreciation, 'n' for the rate of population growth and 'g' for efficiency growth. φ_i, i=1 to 4, capture a weighted technology parameter in growth. This is the unrestricted version of the model where (δ +n+g) appears as a separate determinant of long run growth ($\ln y_t$ - $\ln y_0$).

We assume TFP to be a linear function of infrastructure investment, so ($\ln A_t$) in equation (5) will be functionally related to infrastructure investment. With this specification equation (5) provides the conceptual base for our growth regression.

As with other empirical analysis in this area, adding some control and fixed effect variables to equation (5) will provide us with an empirically testable model of growth determinants. In our case, keeping the specification simple, we only control for country fixed effects as well as macroeconomic stability, which is proxied by the inflation rate. There are undoubtedly other variables that could be controlled for, however provided that those variables excluded from our analysis are not (highly) correlated with those included here, their absence should not significantly affect and bias the results.

3. Sources and analysis of the data

The datasets are based on various sources. The source for the poverty headcount measures is Hassan et. al. (2002). Relative poverty measures are based on Dollar and Kraay (2000).[3] Other poverty proxies, infant and child mortality as well as Human Development Index (HDI), are based on the UNDP Human Development report and were downloaded from its website. Conceicao and Galbraith (1999) is the source for data on inequality. Their estimates of the Theil index are available on a time series basis for a large number of countries[4]. The infrastructure proxies used here for our general dataset are based on Canning (1998)[5]. Other complementary variables we have used for the various model specifications are based on the World Bank World Development Indicators. For our case study on PRC, most of the variables are based on Fan et. al. (2002)[6]. For the inequality index for PRC we have again used the Theil index of inequality, downloaded from the UTIP website.

Table (1) provides the correlation coefficient matrix for the proxies we have used for infrastructure, as well as poverty. Infrastructure proxies are relatively highly correlated. As in most research in this area, we use length of paved road as a proxy for infrastructure. As for poverty, researchers in this area have used various proxies for this, a number of which are included in this study. Those we have are absolute measures of poverty headcounts based on both $1 and $2 a day poverty lines, a relative measure based on income of the poor (the bottom quintile), child and infant mortality rates, and the Human Development Index (HDI). All except the relative measure (Dollar and Kraay, 2000), which has been subject to criticism, have been used in this study. Table (1) shows the relation between these proxies. Correlation coefficients between $1 and $2 a day poverty headcount ratios, HDI and child and infant mortality, as well as between HDI and the $2 a day poverty headcount ratio are relatively high and have the expected sign. In our analysis we report regression results that are based on poverty headcount measures only.

Table (2) presents the correlation coefficient matrix between variables that are considered an important determinant of growth of GDP per capita, as well as a proxy that represents infrastructure per capita and measures of poverty. The second column in this table provides the relationship between the variables that we are most interested in. In particular there is an indication that GDP per capita growth is positively linked with the proxy for infrastructure and HDI, and that it is negatively linked with poverty headcount measures, as well as child mortality. We also use the Theil index as a measure of income distribution, which in this case is negatively linked with growth and positively with the poverty headcount measures.

We first consider the 'trickle down' version of the model of poverty. This is followed by a discussion of the 'ad hoc' version of the model. For both these models we use a dataset that includes both developed and developing countries. Due to the unavailability of some of the key variables in our analysis on a time series basis, particularly poverty indices, the dataset is an unbalanced panel. We also have a similar dataset for all regions in the People's Republic of China (henceforth PRC) that we use as a country case study.

'Trickle down' approach

Equations (2) and (3) form the basis of our regression analysis here. For the 'trickle-down' analysis we provide regression results based on growth and poverty models separately and

[3] Data for these were downloaded from the World Bank website.
[4] The University of Texas Inequality Project (UTIP) has generated a comprehensive data set on Theil indices for a large number of developed and developing countries. Data used in this context is downloaded from its website.
[5] Data for these were downloaded from the World Bank website.
[6] We thank the International Food Research Institute (IFRI) Washington D.C., for providing us with this dataset.

then combine these to determine whether and how infrastructure and poverty are linked. Partly to cope with the gaps, as well as removing cyclical and business cycles from the data, we have converted our data into five-year period averages covering 1960-2000 for our multi-country dataset and 1952-2000 for the case of PRC[7]. Although we have a relatively large number of observations for most variables, for certain key variables there are gaps in the data, which reduce the number of observations and or countries that can be included in our analysis. For our basic regression on growth, the largest dataset that we can use contains 301 observations for 73 countries, including both developed and developing ones.

Table (3) presents the results based on regressions using OLS and a fixed effect panel. Results reported are generally poor, particularly in the case of OLS regressions. Given the heterogeneity in the dataset, OLS is an inappropriate method of data analysis. Panel data is likely to cope better in this context. Columns 3-4 in table (3) report regression results that are based on random and fixed effect methods. Although most of variables in the case of the panel analysis have the right sign theoretically, a large number are statistically insignificant at the appropriate level of significance.

The panel data technique can potentially cope with the problem of heterogeneity. It is however an inappropriate technique in this context. Given the presence of a lagged dependent variable in the regression and the likelihood of endogeneity of independent variables this technique produces biased estimates. To cope with these technical issues we apply the dynamic estimation of panel data or GMM, as first suggested by Arellano and Bond (1991). The basis of this technique is that first the model is first-differenced to remove the country specific dummies from the panel and then appropriate instruments for the variables included are used to produce consistent and efficient estimates of the parameters of the model. Tables (4) and (5) present regression results that are based on variations of this technique. Table (4) reports those that are applicable to both developed and developing countries, whereas table (5) reports those that apply to developing countries only [8].

The results reported in table (4) column (1) indicate that all variables have the right theoretical sign and are generally statistically significant at the relevant level of significance. GMM also reports Wald statistics under the null hypothesis that all parameter estimates except the intercept term are not significantly different from zero, which is comfortably rejected in this case. Diagnostic tests, however, suggest that some of the necessary assumptions do not hold. Sargan's test of over-identifying restrictions cannot be rejected, which may be due to the absence of a homoskedastic error term (first difference) in the regression. In such a case according to Arellano and Bond (1991), Sargan's test does not have an asymptotic chi-squared distribution and therefore it is likely to over-reject in the one-step case. Arellano and Bond's test of absence of second order serial correlation in differenced residuals cannot be accepted either. The presence of second order serial correlation according to Arellano and Bond (1991) produces inconsistent parameter estimates. To correct for this the robust technique that corrects for first order serial correlation is applied in column 2. Although parameter estimates will remain the same using this technique, the t-ratios (and corresponding P-values) of parameter estimates have changed. There is however still a problem with second order serial correlation, as its presence cannot still be rejected. We next apply the two-step method, which according to Arellano and Bond (1991) is better for a test of Sargan's specification. Column 3 reports results based on this variation. The magnitudes of the parameter estimates produced are similar to the previous case, though schooling is still statistically insignificant, but the

[7] For most variables that we have used for PRC in this study however, data coverage starts from the mid 1970s onwards.

[8] The number of developed countries in our dataset and observations that belong to these countries are relatively small and therefore full comparison is not possible here.

infrastructure proxy has now become statistically more significant. The Sargan's test of over-identified restriction, however, cannot still be rejected in this case.

An advantage of GMM is that it can also handle the issue of endogeneity and causation, which is important in our case, particularly in relation to infrastructure and growth. Results reported in columns 1-3 treat these two variables as exogenously determined. Next in column (4) we treat the two variables as endogenous. With this approach although the magnitude of parameter estimates generally remains similar to those reported earlier, their level of statistical significance changes. Diagnostic tests have also been adversely affected; there is evidence of both first and second order autocorrelation in this case.

Columns 5-7 reports results based on the assumptions that both investment share and infrastructure are pre-determined. Again there is not much change in the magnitude of parameter estimates though their significance level has generally improved under this specification. As in the previous case, we apply one-step, robust and two-step procedures. Diagnostic tests suggest that under both one-step and robust, there are problems of both first and second order autocorrelation. Under the two-step procedure, however, the more serious second order autocorrelation is absent and Sargan's test of over-identifying restrictions cannot be accepted in this case.

In all the above specifications, the positive coefficient on infrastructure suggests it plays a positive role in TFP growth and hence in economic growth overall. If anything, this role becomes stronger and more significant with a more rigorous method of estimation and model specification (column 7 table 4 and column 6 table 5). Schooling also appears with the right sign in all these regressions though under the assumption of exogeneity of both investment share and infrastructure, parameter estimates for this variable are not statistically significant at the relevant level of significance. However with a better specification as reported in columns 5-7, our human capital proxy, schooling also becomes statistically significant.

Based on the parameter estimates generated we can derive short-term growth elasticities with respect to both infrastructure and schooling. The growth elasticity, with respect to infrastructure is on average around (0.04) and with respect to schooling is around (0.02).[9]

Other variables in the model also have the right theoretical sign and generally appear as statistically significant also. There is evidence of conditional convergence as indicated by the negative sign and high statistical significance of initial GDP per capita in the model. Macro economic instability as proxied by the rate of inflation also plays a negative and generally significant role in growth.

Table (5) reports similar regressions using a sample of developing countries only. Results reported are very similar to those for the larger dataset that includes a few develped countries as well. As in the previous case, the two-step procedure also seems most appropriate for developing countries. Short run growth elasticities with respect to infrastructure and schooling for developing countries, given parameter estimates reported for the two variables are (0.07) and (0.016), respectively.

For poverty regressions, given our system of equations, we apply the instrumental variable technique. The instruments used in this case are those that appear on the right side of the growth regressions, that is all the independent variables in the growth regressions. Results

[9] The parameter estimate for the infrastructure proxy at the sample mean (schooling) is 0.08 (0.04), based on the results reported in columns 5-7 of table (4) Given the average GDP per capita growth of 1.91 for our data, this gives elasticities of 0.04 and 0.02 approximately. Given the semi-log model specification, the elasticity in this case is λ/y, where λ is the regression coefficient and y is the average of the dependent variable.

based on this estimation method are reported in table (6) using the poverty headcount measure as the poverty variable.

The regression model used here is a simple one, regressing a poverty proxy on GDP per capita growth, as well as other factors that may have an effect on poverty. We however treat GDP per capita growth as endogenously determined by our growth regression above. Using an instrumental variable panel data regression allows us to take into account this endogeneity. Table (6) presents results that are based on poverty regressions using the poverty headcount measures (at $1 a day and $2 a day poverty lines) as the dependent variable. Based on the Hausman specification test that we apply here, the random effect panel seems to be the appropriate technique. In addition to growth, we have also tried to check whether inequality has any effect on poverty. Given that most poverty measures are at least partly constructed using a Gini coefficient, its use as an explanatory variable in a poverty regression is inappropriate. In this case we use an alternative measure of inequality, the Theil index, which is also available on a more regular basis than the Gini measure.

In all the regression results produced in table (6), GDP per capita growth has a negative and significant effect on poverty; this is the case irrespective of the poverty measure used. As far as the inequality index is concerned, our analysis suggests that there is a statistically significant and direct relationship between inequality and poverty. The inequality proxy we have used here is the initial (1970) level of the Theil index rather than its periodic level. This either suggests that countries that start with a higher level of inequality suffer more poverty or alternatively this initial level catches the lag effect of inequality on poverty.

There is no indication that when poverty is measured by the $1 a day line, there is any regional difference in the data. When we use a $2 a day poverty headcount as the dependent variable however, there appear to be some regional differences in this respect; Africa and Asia seem to be doing relatively badly in poverty terms compared with other regions, allowing for all other factors. Poverty reduction elasticities with respect to growth are (-1.03) and (-0.43) for the case of $1 and $2 a day poverty headcounts, respectively[10].

Given the positive and significant link between infrastructure and growth on the one hand and the negative and significant relationship between poverty and growth on the other, and given the model structure, there will be a negative link between poverty and infrastructure. There is also similar link between poverty and human capital as proxied by schooling, in this case. However, the model structure is such that the direct impact of neither of these variables can be quantified; the 'ad hoc' modelling discussed in the next section allows us to capture this directly from the results reported.

'Ad hoc' specification

The generic empirical model that we have used here follows equation (4), although it differs in the more rigorous applications where G is not actual growth, but instruments for growth. The results based on a simple 'ad hoc' model are reported in table (7). Columns 1-5 in table (7) show regression results using $1 a day poverty headcounts, whereas those in columns 6-10 show the same using $2 a day poverty headcounts, as the dependent variable. We also include a dummy to capture differences in the way poverty headcounts are measured; whether they are based on income or expenditure[11]

[10] The elasticities are based on average data for developing countries in our sample for 1996-2000.

[11] There is general agreement in the literature is that poverty headcount measures based on income are likely to underestimate the extent of poverty and a more accurate method would be to base these measures on the expenditure of households. We test this by applying a dummy for the presence of income based poverty estimates. In the context of the $2 a day poverty headcount, in particular, this view is generally confirmed;

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We apply different estimation techniques to determine the robustness of the parameter estimates for the variables included in the regression equation. The techniques applied are ordinary list square (OLS), panel fixed effect (PFE), panel random effect (PRE), panel instrumental variable fixed effect (PIVFE), as well as panel instrumental variable random effect (PIVRE). Given the heterogeneity of data in our dataset, OLS is unlikely to be an appropriate method of estimation. Use of various techniques available for panel data are likely to be more appropriate in this context. The Hausman specification test in this case suggests that the fixed effect panel is a more appropriate method of estimation than the random effect.

In addition to heterogeneity, endogeneity is also an issue that should be addressed. The problem of endogeneity is likely to arise due to the presence of growth of GDP per capita as an explanatory variable. To correct for this, we apply an instrumental variable technique to the panel data using both fixed and random effects. The instruments we use for growth include its first and second lags as well as the logarithm of the share of gross capital formation in GDP. In addition to the variables reported in table (7) we have also controlled for other variables (inflation rate to capture macroeconomic stability) and regional dummies. These other variables are not been reported, since they are statistically insignificant.

In the case of the poverty ratio based on $1 a day, the results indicate that there is a statistically significant negative link between the poverty ratio and growth of GDP per capita. This is the case for all different techniques of estimation at the usual significance level, except for the case of PFE where the parameter estimate is statistically significant at just over 11%. For the $2 a day poverty ratio, there is both a reduction in the magnitude of the parameter estimate for this variable, as well as its statistical significance; it is only statistically significant in the case of OLS and PIVRE.

Given the Hausman specification test that suggests fixed effect to be a more appropriate test in this case, combined with the endogeneity of growth of GDP, our preferred technique of estimation is PIVFE. This corresponds to the results generated in columns 4 and 9 for poverty headcounts based on $1 and $2 a day lines, respectively.

Another variable that is likely to impact on poverty is the way in which income is distributed. The proxy we have used is the initial level of the Theil index. For both poverty ratios, this proxy has the right theoretical sign and is generally statistically significant, at the relevant significance level. This suggests that the initial level of inequality has a detrimental effect on the level of poverty.

We test for the impact of infrastructure on poverty by including infrastructure as a separate independent variable. However on its own although it generally has the right theoretical sign, it is never significant. Nonetheless there appears to be a complementarity between our infrastructure proxy and our human capital proxy, school enrolment. This is captured by the interactive term in all regressions reported here. On their own neither of infrastructure or schooling perform well when both appear in the regression, although their joint significance in the regression is verified by both F and Wald test, as well as by goodness of fit. This indicates the possible problem of multicollinearity. The interpretation we offer is that infrastructure opens up opportunities that those who have a minimum amount of human capital are better placed to take advantage of. In all the regressions reported using different techniques of estimation, this interactive term is negative and highly statistically significant; a more fully specified poverty model is unlikely to produce a statistically insignificant result in

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parameter estimates for this dummy are positive and significant for in all cases, except OLS. Inclusion this dummy is expected to capture the differences between the two measures.

the case of this variable. Based on the parameter estimate for this variable, the poverty elasticity with respect to infrastructure/schooling can be quantified. In the case of the $1 a day poverty headcount, elasticity of poverty with respect to infrastructure or schooling is (-0.35) on average. For the $2 a day poverty headcount, poverty elasticity with respect to the two proxies is similar at around (-0.53) on average.[12]

Given the interaction of infrastructure with schooling in our analysis here, the poverty elasticity with respect to infrastructure (schooling) varies directly with schooling (infrastructure). For example, our results suggest that, for the $1 poverty headcount ratio, if schooling increases by 25% the poverty elasticity with respect to infrastructure increases to (-0.38). An increase of 50% or 75% raises this to (-0.40) and (-0.45) respectively. Regarding the $2 poverty headcount ratio, for the same rate of change in schooling, poverty elasticities with respect to infrastructure rise to (-0.60), (-0.66) and (-0.74) respectively.

In addition to the use of poverty ratios, we have tried other proxies that are likely to capture poverty in a country; these (not reported) include child and infant mortality and the human development index. In all cases, the only variable that is highly statistically significant and has the expected sign is the interactive term. In the case of other variables, most parameter estimates are either statistically insignificant and or have the 'wrong' sign.

Goodness of fit in all cases is generally higher for regressions using the $2 a day poverty line as dependent variable rather than the $1 a day poverty line. Inspection of the data on the two measures indicates that the two are not linearly related and therefore require a different specification. This is to be expected since those below the $1 a day line are likely to include larger proportion of the poor who are rural-based and therefore more likely to be affected by rural activities rather than those that apply to the whole economy. Results based on rural poverty in PRC discussed next give some credence to this hypothesis.

In summary, our results for the link between infrastructure and poverty reduction suggest that it only operates in an environment in which infrastructure facilities and schooling grow together. This result from our cross-country analysis has also been found in some country cases and to test its robustness here we apply a similar ad hoc approach to data from PRC.[13]

4. Case study of PRC

To investigate further the potential impact of infrastructure on poverty we consider the case of rural poverty in PRC.[14] Data available are on a time series basis for all 29 regions. We convert the time series data into a five-year average dataset. There are gaps in data coverage and as a result the dataset we use in this case is also an unbalanced panel. The maximum number of observations we have is 109 that cover the 29 regions of PRC. Data limitations only allow us to consider the 'ad hoc' version of the model.

Given that the data covers rural poverty, we have tried to use explanatory variables that are more appropriate in this context. Given the importance of agriculture to the rural sector, we have used growth of agricultural output as a proxy for the role that growth in general has in poverty reduction. For the same reason other variables included are also rural specific;

[12] Elasticities generated here are based on average data for relevant variables for developing countries for 1991-1995 period; this is the last date for which the infrastructure proxies we have used in this study are available.
[13] For the Philippines, Balisacan and Pernia (2003) report that whilst roads are negatively related to the income of the poor, if they are interacted with a schooling measure this term is positively and strongly significantly related to the income of the poor.
[14] The dataset that we have on PRC covers rural poverty and for that we can only investigate the potential link for rural poverty.

these include schooling as well as a proxy for infrastructure. For the latter we have used electricity consumption, since this is the only rural-based infrastructure proxy available with a wide coverage. Others such as length of roads are either applicable to the country in general or have a very narrow coverage.

Regression results based on this specification are reported in table (8). As in the previous case to test the robustness of the parameter estimates, we apply different estimation techniques to the data. Columns 1-3 report results that are based on OLS. A-priori however, OLS might not be an appropriate technique to use given the data heterogeneity for different regions in PRC. Columns 4-10 report results that use variants of the panel data technique, - fixed effect, random effect, and instrumental variable fixed effect, as well as the instrumental random effect. In the latter two we treat growth of agricultural output per capita as an endogenous variable. The Hausman specification test in all cases suggests that the random effect is a more appropriate technique to use rather than the fixed effect.[15] The dependent variable in all regressions is the officially reported poverty headcount ratio in rural PRC; other poverty proxies available have a very limited coverage.

We have applied a similar specification to the PRC data as applied to the larger dataset reported in table (7). In all different specifications reported, growth of agricultural output per worker appears with the right theoretical sign and is statistically significant in all cases. The magnitude of the parameter estimate for this variable remains relatively stable using different estimation techniques. When we add a schooling variable separately, in addition to the growth variable, as column 2 shows it has the expected sign and is also highly significant. Adding the infrastructure proxy to this, as in column 3, however has an adverse effect on the magnitude and statistical significance of schooling; infrastructure also appears as statistically insignificant though it has the expected theoretical sign. The same occurs when we first add infrastructure to the model and then add schooling. The parameter estimate for infrastructure on its own has the expected theoretical sign and is statistically significant; once schooling is added, both the magnitude and statistical significance of infrastructure are adversely affected. This may indicate possible multicolinearity between the two; the correlation coefficient for the two is close to 0.7. This problem persists using a different method of estimation as reported in columns 5-7; in all these the two variables appear with the theoretically expected sign but both are statistically insignificant. The goodness of fit combined with the F and Wald test however confirm their role in the regressions. Columns 8-10 give the results that are based on the interaction of the two variables.[16] In all these the interactive term appears with the expected sign and is highly statistically significant. We also tried using a proxy for inequality that conforms to the regional data. The one available that we have used in our analysis is the Theil index. In all regressions that we ran using this proxy, the parameter estimate was found to be highly statistically insignificant, though generally it appears with the expected sign.

Based on the parameter estimates for the infrastructure and human capital proxies we can generate an average elasticity of poverty with respect to infrastructure and or schooling. Calculation of poverty elasticities using the average parameter estimates reported in columns 7-10 gives an average elasticity of around (-0.28) with respect to both these proxies. This is not that different from the same elasticity for the larger dataset and confirms the robustness of the earlier result. Given the interaction between infrastructure and schooling, as in the case of the larger dataset, the poverty elasticity with respect to infrastructure varies directly with schooling.

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[15] For the larger dataset, the fixed effect technique was generally found to be more appropriate than the random effect. However one can argue that although there are likely to be regional variations in PRC, these variations are likely to be different from and possibly less than those that exists between different countries.
[16] As in the case of the larger dataset, this is generated as (schooling *infrastructure). The logarithm of this interaction term appears in the regression results reported here.

5. Conclusions

There are controversies that surround both the theoretical and empirical analysis of the determinants of poverty. In this paper we have attempted to apply different theoretical and empirical techniques to account for the link between poverty and infrastructure. The results reported here provide empirical support for the view that infrastructure impacts negatively on poverty both indirectly through growth and directly when it interacts with human capital. However our results provide no evidence that infrastructure on its own has any direct poverty reduction impact. This proposition is supported by data for a group of developed as well as developing countries, and is further verified by the case study of rural poverty in PRC.

The magnitude of the poverty elasticity generated in this paper, with respect to both infrastructure and human capital is not negligible. Our results based on the 'ad hoc' specification of poverty suggest that on average a 1% point increase in infrastructure stock per capita, holding human capital constant, is associated with a 0.35% reduction in the poverty ratio, when poverty is measured by $1 a day poverty headcount or 0.52%, when it is measured by $2 a day poverty headcount. The same level of increase in infrastructure would have a much larger effect when it is also accompanied by an increase in human capital. Our analysis suggest that an increase in human capital (proxied by secondary schooling) by 25% would increase the poverty elasticity with respect to infrastructure by around 8% on average. A combination of an increase in human capital investment and infrastructure therefore could have a stronger impact on poverty reduction than either alone. This is a direct effect and the total effect will be greater by incorporating other poverty determinants.[17].

Based on the results generated, we further investigate the magnitude of changes required in infrastructure on its own and when it is also combined with changes in human capital, in order to reduce poverty in selected countries. As a reference point we use the average poverty for our sample (for both $1 a day and $2 a day poverty headcounts) for the most recent year that we have comparable data.[18] We then consider countries that suffer from a higher level of poverty than the average for our sample and ask what changes they require in either infrastructure on its own or combined with schooling in order to bring their level of poverty to the sample average.

The results are only illustrative, but indicate the very large orders of magnitude required if poverty reduction is to be through infrastructure improvements alone. For example, if we take the sample average headcount at $2 per day of 44%, then for India at actual schooling levels and values of other explanatory variables, our infrastructure proxy must increase by 35% to bring the poverty headcount in India to the sample average of 44% as compared with the actual of 53%; if the schooling indicator improves by 25%, the infrastructure increase required is still very substantial at 31%. For Bangladesh the comparable figures are considerably lower, with a required infrastructure increase of only 13% with no improvement in schooling and 11% with a 25% improvement in schooling. However, these relatively low figures reflect the fact that the poverty headcount in Bangladesh of 47% is already close to the sample average. The figures for PRC are intermediate between those for India and Bangladesh with a 27% increase in the infrastructure variable required to achieve a fall in the poverty headcount from 50% to 44% (with no improvement in schooling) and a 23% increase (with a 25% improvement in schooling).

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[17] Variables that affect poverty based on our ad hoc strategy also include growth of GDP per capita and inequality. Given the possibility of interaction between these and infrastructure and schooling, the individual effects are not generally additive. In the case of growth, in particular, it is likely to interact directly and indirectly with both infrastructure and schooling, in which case its effect cannot easily be separated from that of those variables.

[18] For some key variables, such as the infrastructure proxies we have used in this paper, data is available only until 1995.

Hence whilst infrastructure investment clearly has a role in a poverty reduction strategy this type of analysis warns of the very large increases in infrastructure activity in physical (and by implication financial) terms required to affect substantial poverty reduction. The simple implication is that growth, plus factors like improvements in infrastructure and schooling, will be required for rapid reductions in poverty.

Table (1): Correlation coefficient matrix for proxies for infrastructure and poverty indices

		1	2	3	4	5	6
1	**Mainline Telephone**	1					
2	**Length of Paved Road**	0.7928	1				
3	**Length of Rail**	0.6609	0.7955	1			
4	**Length of All roads**	0.7899	0.9012	0.8091	1		
5	**Electricity consumption**	0.928	0.8654	0.7056	0.8505	1	
6	**Poverty ($1 a day)**	-0.4755	-0.2106	-0.024	-0.1506	-0.3834	1
7	**Poverty ($2 a day)**	-0.4923	-0.086	0.0646	-0.0925	-0.3435	0.8775

Table (2): Correlation coefficient matrix for variables used in growth and poverty regressions

		1	2	3	4	5	6	7	8
1	**GDP per capita**	1							
2	**GDP per capita growth**	0.0695	1						
3	**Investment share**	0.259	0.4147	1					
4	**Schooling**	0.6011	0.3062	0.3552	1				
5	**(σ + g +n)**	-0.0509	-0.4145	-0.2571	-0.3893	1			
6	**Infrastructure per capita**	0.6092	-0.1451	0.1202	0.3158	0.081	1		
7	**Theil index**	-0.2509	-0.1328	-0.2213	-0.3009	0.1984	0.0252	1	
8	**Poverty ($1 a day)**	-0.5872	-0.2894	-0.2878	-0.5907	0.204	-0.1	0.2278	1
9	**Poverty ($2 a day)**	-0.808	-0.1597	-0.3208	-0.6272	0.2026	-0.3387	0.2856	> 0.8786

Table (3): Growth regressions based on OLS and Panel data techniques

Variables		Method of Estimation		
	OLS	OLS	PRE [(a)]	PFE [(b)]
	1	2	3	4
Initial GDP per capita	0.004	0.007	-0.01	-0.212
t-ratio	0.497	0.826	-0.914	-8.916
p value	0.62	0.41	0.361	0
Investment Share	0.149	0.141	0.152	0.173
t-ratio	10.206	9.59	9.175	8.924
p value	0	0	0	0
(σ + g +n)	-0.03	-0.028	-0.027	-0.041
t-ratio	-3.486	-3.092	-2.622	-3.417
p value	0.001	0.002	0.009	0.001
Schooling	-0.013	-0.023	-0.021	0.006
t-ratio	-2.067	-3.386	-2.533	0.572
p value	0.04	0.001	0.011	0.568
Consumer Price Index	0	0.001	0	-0.002
t-ratio	0.356	0.829	-0.299	-1.526
p value	0.722	0.408	0.765	0.128
Infrastructure per capita	-0.014	-0.004	0.007	0.054
t-ratio	-2.034	-0.507	0.719	3.083
p value	0.043	0.613	0.472	0.002
Constant	-0.493	-0.432	-0.266	1.287
t-ratio	-5.802	-4.825	-2.392	6.345
p value	0	0	0.017	0
Regional dummies				
Africa		-0.009	-0.039	
t-ratio		-0.386	-1.235	
p value		0.7	0.217	
Asia		0.049	0.032	
t-ratio		1.844	0.919	
p value		0.066	0.358	
Latin America		0.023	0.005	
t-ratio		1.012	0.162	
p value		0.312	0.871	
Number of observations	301	301	301	301
Number of countries	73	73	73	73
F test	22.77	17.19	114.91	27.42
p-value	0	0	0.215	0
Adj. R-squared	0.3034	0.3269	0.4337	0.4256

Note:

[(a):] Panel data Random Effect
[(b):] Panel data Fixed Effect

Table (4): Growth regressions using dynamic panel data estimation (GMM): All countries *

Variables	One Step [a]	Robust	Two Step	Robust	One Step	Robust	Two Step-
		Exogenous [b]		Endogenous [c]		Pre-determined [d]	
	1	2	3	4	5	6	7
Lag GDP Growth	-0.213	-0.213	-0.174	-0.067	-0.1	-0.1	-0.084
t-ratio	-3.892	-3.167	-3.427	-0.959	-1.635	-1.375	-3.997
p value	0	0.002	0.001	0.338	0.102	0.169	0
Initial GDP per capita	-0.28	-0.28	-0.326	-0.239	-0.242	-0.242	-0.254
t-ratio	-9.059	-4.613	-7.292	-4.632	-7.637	-4.938	-12.013
p value	0	0	0	0	0	0	0
Investment Share	0.208	0.208	0.215	0.198	0.149	0.149	0.149
t-ratio	9.62	9.052	11.327	4.679	5.507	4.529	25.112
P value	0	0	0	0	0	0	0
Lag Investment Share				-0.11	-0.054	-0.054	-0.054
t-ratio				-2.984	-2.232	-1.823	-13.904
P value				0.003	0.026	0.068	0
(σ + g +n)	-0.023	-0.023	-0.021	-0.028	-0.034	-0.034	-0.031
t-ratio	-1.834	-1.836	-1.912	-2.221	-2.627	-2.49	-6.018
p value	0.067	0.066	0.056	0.026	0.009	0.013	0
Schooling [e]	0.027	0.027	0.011	0.042	0.04	0.04	0.043
t-ratio	1.533	1.473	0.727	2.119	2.174	2.103	8.575
p value	0.125	0.141	0.467	0.034	0.03	0.035	0
Consumer Price Index	-0.006	-0.006	-0.005	-0.003	-0.003	-0.003	-0.003
t-ratio	-2.508	-1.958	-2.013	-1.278	-1.492	-1.453	-5.047
p value	0.012	0.05	0.044	0.201	0.136	0.146	0
Infrastructure per capita [f]	0.04	0.04	0.047	0.096	0.081	0.081	0.08
t-ratio	1.609	2.277	3.601	2.359	2.601	2.182	10.947
p value	0.108	0.023	0	0.018	0.009	0.029	0
Constant	0.003	0.003	0.006	0	-0.001	-0.001	-0.002
t-ratio	0.443	0.347	1.025	-0.026	-0.219	-0.196	-1.591
p value	0.658	0.729	0.305	0.979	0.826	0.845	0.112
Number of observations	210	210	210	203	203	203	203
Number of countries	64	64	64	62	62	62	62
Wald test	217.41	233.66	547.52	132.24	145.69	126.95	7380.58
Sargan test	0.0062		0.025		0.003		0.3108
1st order serial correlation	0.4442	0.4415	0.7683	0.005	0.0011	0.0034	0.0153
2nd order serial correlation	0.0047	0.0385	0.0607	0.056	0.0206	0.0947	0.1181

Note:

*** : All variables are first difference of respectable variables specified; see Arellano and Bond (1992) for more details**

(a): For details on one step, two step and robust, see Arellano and Bond (1992)

(b): Both investment share and infrastructure assumed to be exogenously determined.

(c): Both investment share and infrastructure assumed to be endogenous.

(d): Both investment share and infrastructure assumed to be pre-determined.

(e); Fraction of population with tertiary education.

(f): Length of road per capita.

Table (5): Growth regressions using dynamic panel data estimation (GMM): Developing countries

Variable	One Step	Robust	Two Step	One Step	Robust	Two Step
	Exogenous			Pre-determined		
	1	2	3	4	5	6
Lag GDP Growth	-0.219	-0.219	-0.173	-0.095	-0.095	-0.089
t-ratio	-3.903	-3.1	-3.396	-1.529	-1.296	-6.081
p value	0	0.002	0.001	0.126	0.195	0
Initial GDP per capita	-0.276	-0.276	-0.312	-0.243	-0.243	-0.25
t-ratio	-8.593	-4.279	-6.635	-7.302	-4.52	-15.502
p value	0	0	0	0	0	0
Investment Share	0.213	0.213	0.229	0.156	0.156	0.153
t-ratio	9.594	9.137	12.33	5.689	4.898	31.433
P value	0	0	0	0	0	0
Lag Investment Share				-0.055	-0.055	-0.053
t-ratio				-2.247	-1.966	-17.878
p value				0.025	0.049	0
(σ + g +n)	-0.04	-0.04	-0.045	-0.044	-0.044	-0.046
t-ratio	-2.505	-2.709	-3.901	-2.742	-3.026	-13.135
p value	0.012	0.007	0	0.006	0.002	0
Schooling	0.014	0.014	-0.005	0.027	0.027	0.027
t-ratio	0.739	0.742	-0.347	1.351	1.301	6.036
p value	0.46	0.458	0.729	0.177	0.193	0
Consumer Price Index	-0.006	-0.006	-0.005	-0.004	-0.004	-0.004
t-ratio	-2.427	-1.864	-2.076	-1.58	-1.454	-5.874
p value	0.015	0.062	0.038	0.114	0.146	0
Infrastructure per capita	0.044	0.044	0.055	0.102	0.102	0.113
t-ratio	1.764	2.499	4.176	3.477	2.518	9.609
p value	0.078	0.012	0	0.001	0.012	0
Constant	0.005	0.005	0.007	0.001	0.001	0.002
t-ratio	0.695	0.573	1.129	0.146	0.132	2.066
p value	0.487	0.567	0.259	0.884	0.895	0.039
Number of observations	195	195	195	191	191	191
Number of countries	56	56	56	56	56	56
Wald test	204.47	220	535.11	142.64	114.65	43938.64
Sargan test	0.022		0.076	0.0103		0.6155
1st order serial correlation	0.3739	0.3699	0.4919	0.006	0.0045	0.012
2nd order serial correlation	0.0039	0.0297	0.0303	0.0242	0.0901	0.1017

Table (6): Poverty regressions using poverty headcounts as a measure of poverty

Variable	Estimation method: Instrumental variable Panel data (random effect)				
	Poverty headcount				
	$1 a day		$2 a day		
	All	Dev.	All	Dev	All
	1	2	3	4	5
GDP per capita growth	-2.07	-1.98	-2.97	-2.60	-2.25.
	-2.598	-2.492	-2.983	-2.514	-2.224
	0.009	0.013	0.003	0.012	0.026
Theil inequality index	2.77	2.80	4.88	4.40	3.82
	3.61	3.601	3.91	3.44	3.56
	0	0	0	0.001	0
Regional Dummies:					
Africa					23.242
					1.864
					0.062
Asia					26.98
					2.454
					0.014
Latin America					8.921
					0.81
					0.418
Constant	3.62	3.35	14.142	18.696	1.385
	0.725	0.661	1.829	2.259	0.143
	0.469	0.508	0.067	0.024	0.886
R-Sq	0.54	0.5288	0.604	0.5238	0.6841
Number of observations	78	77	93	81	93
Number of Countries	34	33	39	33	39
Wald test	22.12	20.9	26.95	19.28	46.2
P-value	0	0	0	0.0001	0
Hausman Specification Test (P-values)	0.0012		0		
Condition Tested	RE v FE		RE v FE		

Table (7): Poverty regression: Dependent variable is poverty ratio

Variables	Method of estimation									
	Poverty headcount: $1 a day					Poverty headcounts: $2 a day				
	OLS (1)	PFE (2)	PRE (3)	PIVFE (4)	PIVRE (5)	OLS	PFE	PRE	PIVFE	PIVRE
	1	2	3	4	5	6	7	8	9	10
GDP per capita growth	-1.491	-0.543	-0.707	-1.412	-2.029	-1.004	0.366	0.128	-1.015	-1.821
t-ratio	-3.035	-1.604	-2.204	-2.19	-2.797	-2.057	1.29	0.447	-1.568	-2.486
p-value	0.003	0.115	0.028	0.029	0.005	0.041	0.2	0.655	0.117	0.013
Initial inequality (6)	0.471	0.182	0.274	0.111	0.843	0.991	0.647	0.895	1.858	169.071
t-ratio	1.073	0.406	0.727	1.776	1.778	2.146	1.334	2.199	2.853	3.184
p-value	0.286	0.687	0.467	0.076	0.075	0.034	0.186	0.028	0.004	0.001
Poverty measure (7)	-2.737	8.815	4.278	14.351	6.989	-8.608	15.951	7.958	23.512	12.064
t-ratio	-0.826	2.639	1.463	3.271	1.844	-2.346	4.233	2.382	4.921	2.756
p-value	0.411	0.011	0.143	0.001	0.065	0.02	0	0.017	0	0.006
Interactive term (8)	-4.76	-6.509	-7.227	-7.12	-6.521	-9.413	-12.688	-13.042	-15.137	-12.755
t-ratio	-4.25	-4.35	-6.089	-3.419	-4.539	-10.311	-7.91	-11.373	-6.899	-8.996
p-value	0	0	0	0.001	0	0	0	0	0	0
Intercept	3.583	-7.267	-2.236	-16.297	-5.718	13.211	-10.021	-3.731	-22.586	-7.681
t-ratio	0.664	-1.379	-0.436	-2.274	-0.973	2.917	-2.159	-0.784	-3.659	-1.349
p-value	0.508	0.174	0.663	0.023	0.331	0.004	0.034	0.433	0	0.177
Number of observations	103	103	103	92	92	151	151	151	132	132
Number of countries	45	45	45	43	43	63	63	63	59	59
F/Wald test	9.09	8.67	44.04	485.84	27.72	50.78	24.53	132.39	2375.54	94.97
p-value	0	0	0	0	0	0	0	0	0	0
R-squared	0.2706	0.1162	0.1875	0.1142	0.1967	0.5818	0.3928	0.4903	0.4017	0.486

Notes:

1. Ordinary Least Square
2. Panel Fixed Effect

3. Panel Random Effect
4. Panel Instrumental Variable Fixed Effect
5. Panel Instrumental Variable Random Effect
6. This is based on the Theil index.
7. A dummy variable that is set to 1 if poverty headcount measure is based on income rather than expenditure.
8. Constructed by multiplying infrastructure proxy (length of road per population) to the human capital proxy (secondary school education)

Table (8): Factors affecting poverty in rural PRC
Dependent variable is rate of rural poverty (%)

Variables					**Method of Estimation**					
	OLS	*OLS*	*OLS*	*PRE*	*PFE*	*PIVFE*	*PIVRE*	*PIVFE*	*PIVRE*	*PRE*
	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**
Growth of agriculture output per worker [(a)]	-0.261	-0.196	-0.159	-0.108	-0.096	-0.134	-0.170	-0.151	-0.176	-0.106
t-ratio	-4.402	-3.370	-2.630	-2.330	-2.000	-2.380	-2.830	-2.490	-2.900	-2.290
p-value	0.000	0.001	0.010	0.004	0.049	0.017	0.005	0.013	0.004	0.022
Rural Schooling [(b)]		-7.895	-3.807	-4.894	-8.418	-8.713	-5.317			
t-ratio		-4.040	-1.33	-1.440	-1.580	-1.63	-1.550			
p-value		0.000	0.185	0.149	0.117	0.104	0.121			
Rural Infrastructure per worker [(c)]			-2.481	-2.441	-1.219	-1.025	-2.029			
t-ratio			-1.940	-1.490	-0.042	-0.35	-1.210			
p-value			0.055	0.136	0.674	0.724	0.226			
Interactive term [(d)]								-3.659	-3.013	-3.194
t-ratio								-4.080	-4.470	-4.840
p-value								0.000	0.000	0.000
Constant	18.371	31.570	14.105	14.699	25.533	27.940	18.484	9.461	10.950	8.862
t-ratio	10.298	8.610	1.470	1.250	1.300	1.410	1.530	4.160	4.260	3.910
p-value	0.000	0.000	0.147	0.211	0.196	0.158	0.127	0.000	0.000	0.000
Number of observations	109	108	108	108	108	108	108	108	108	108
Number of Regions	29	29	29	29	29	29	29	29	29	29
F/ Wlad test	19.38	18.95	14.22	33.78	7.46	358.99	35.84	357.68	36.37	33.90
P-value	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
R-squared	0.145	0.251	0.271	0.285	0.265	0.273	0.289	0.288	0.290	0.285

Note:

(a): Nominal figures are converted into constant one using CPI. We have also used agriculture GDP instead of agriculture output; results are very close.

(b): Percentage of rural population rural population with high school education.
(c): Electricity consumption per worker in rural PRC.
(d): Constructed as Schooling times rural infrastructure per worker.

References:

Agenor, P-R. (forthcoming): 'Does globalisation hurt the poor?' *Journal of International Economics and Policy*

Arellano, M and Bond, S (1991) 'Some Tests of Specification for Panel Data: Monte Carlo evidence and application of employment equations' *Review of Economic Studies,* vol 58, no 2.

Balisacan, A and Pernia, E (2003) 'Poverty, inequality and growth in the Philippines' in E.Pernia and A.Deolalikar (eds) *Poverty, Growth and Institutions*, Palgrave, Hampshire.

Calderon, C and Serven, L (2004) 'The effects of infrastructure development on growth and income distribution' mimeo World Bank, downloaded from www.worldbank.org

Canning, D. (1998),"A database of world stock of infrastructure, 1950-1995", *World Bank Economic Review*, World Bank, Washington DC

Conceicao, P. and J.K. Galbraith, "Constructing long and dense time-series of inequality using the Theil index", UTIP Working Paper, No. 1 (1999).

Dollar, D. and A. Kraay, (2000), 'Growth Is Good for the Poor' mimeo Development Research Group, World Bank, downloaded from www.worldbank.org.

Fan, S., L. Zhang and X. Zhang (2002): 'Growth, inequality, and poverty in Rural China: the role of infrastructure', Research Report 125, International Food Research Institute (IFRI), Washington D.C.

Hanmer, L. and F. Naschold, (2000), 'Attaining the International Development Targets: Will Growth Be Enough', *Development Policy Review*, vol18 11-36.

Hassan, R., M.G. Quibria and Y.S. Kim, 'Poverty and Policy: What do data tell us?', mimeo ADB Institute, Tokyo.

Mankiw, N., D. Romer and D. Weil, (1992) 'A Contribution to the Empirics of Economic Growth', Quarterly Journal of Economics, CVII, , 407-37.

Nonneman, W. and P. Vanhoudt, (1996) 'A Further Augmentation of the Solow Model and the Empirics of Economic Growth for OECD Countries', *Quarterly Journal of Economics*, Aug, 943-53.

Ravallion, M and Jalan, J (1999) 'China's lagging poor areas' *American Economic Review,* vol 89, no 2, 301-305.

Temple, J. and P.A. Johnson, (1995) 'Social capabilities and economic growth', *Quarterly Journal of Economics*, 965-990.

van der Linden G (2004) 'Laying the foundations for the future: infrastructure's essential role' speech to the Royal Society, London 27th October, downloaded from www,adb.org