The Return to Foreign Aid

Carl-Johan Dalgaard
University of Copenhagen and CEPR

Henrik Hansen
University of Copenhagen and DERG

March 2016

Abstract

We estimate the average rate of return on investments financed by foreign aid and by domestic resource mobilization, using aggregate data. Both returns are expected to vary across countries and time. Consequently we develop a correlated random coefficients model to estimate the average returns. Across different estimators and two different data sources for GDP and investment our findings are remarkably robust; the average gross return on "aid investments" is about 20 per cent. This is in accord with micro estimates of the economic rate of return on aid projects and with aggregate estimates of the rate of return on public capital.

Keywords: Productivity, growth accounting, foreign aid, random coefficients, panel data.
JEL classification: O47, F35, C23

Corresponding author: Henrik.Hansen@econ.ku.dk. Department of Economics, University of Copenhagen, Øster Farimagsgade 5, Building 26, DK-1353, Denmark.

> 'Developing countries are not starved of capital because of credit-market frictions. Rather, the proximate causes of low capital-labor ratios in developing countries are that these countries have low levels of complementary factors, they are inefficient users of such factors (as Lucas [1990] suspected), their share of reproducible capital is low, and they have high prices of capital goods relative to consumption goods.
>
> As a result, increased aid flows to developing countries are unlikely to have much impact on capital stocks and output, unless they are accompanied by a return to financial repression, and in particular to an effective ban on capital outflows in these countries. Even in that case, increased aid flows would be a move towards inefficiency, and not increased efficiency, in the international allocation of capital.' (Francesco Caseli and James Feyer in 'The Marginal Product of Capital', *Quarterly Journal of Economics*, 2007, Vol. 122; quote from the conclusion, pages 565-66.)

1 Introduction

The Asian Infrastructure Investment Bank (AIIB) was formally established and started operation on December 25, 2015. The authorized capital stock of the AIIB is USD 100 billion, which may be compared to the Asian Development Bank's capital base of some USD 160 billion and the World Bank's of USD 223 billion. According to the AIIB homepage (euweb.aiib.org) the bank "will focus on the development of infrastructure and other productive sectors in Asia, including energy and power, transportation and telecommunications, rural infrastructure and agriculture development, water supply and sanitation, environmental protection, urban development and logistics, etc." Interestingly, if Caseli and Feyrer are correct in their assessment of aid flows to developing countries, the focus of this large new international development bank is misplaced and the new funding is at risk of being wasted. The argument is quite simple, if the marginal productivity of physical capital (MPK) is equal across rich and poor countries, as found in Caseli and Feyrer (2007), then foreign aid directed towards capital investments in poor countries will have a very low return because successful aid investments will simply replace private capital.

This discrepancy between current development research and development practise is baffling. Donors appear to ignore the results of top researchers and with the establishment of the AIIB they do the exact opposite of the scholarly recommendations. Even if the establishment of the AIIB is seen as a mainly politically motivated move by China, the size of the investment is far too large to be seen as a symbolic gesture. Thus, policy makers in AIIB's 57 member countries must disagree with Caseli and Feyrer (2007), and by implication with Lucas (1990).

In this paper we seek to reconcile the discrepancy. We do this by noting that Caseli and Feyer's conclusion about aid flows does not follow directly from the equality of the returns to aggregate capital (the MPK) across rich and poor countries. Specifically, if aid investments are focused on projects for which international private capital flows cannot generate equal returns across developed and developing countries and *government* borrowing on the international commercial credit market is restricted, the marginal productivity of aid investment may well be high in countries with concurrent low marginal productivity of private capital.

A classical way of establishing the return on aid financed investments is to examine project level economic rates of return. At this level aid investments have long been found to yield

Table 1: Median economic rates of return of World Bank evaluated operations

Sector Board	Projects	Share (%)	ERR[a] (%)	RERR[b] (%)
Energy and Mining	168	25	18	16
Environment	13	2	17	17
Communications Technology	27	4	26	25
Rural Sector	208	31	21	18
Transport	165	24	30	29
Urban Development	40	6	20	17
Water Supply and Sanitation	59	9	13	10
Overall Result	680	100	21	19

[a] Economic rate of return at appraisal, [b] Revised economic rate of return at appraisal.
Note: The data are for Fiscal Year 1994-2003 exits. They represent a partial lending sample (130 out of 293) and reflect all Operations Evaluation Department (OED) project evaluations through December 31, 2003. Figures exclude projects not rated. OED reporting of rates of return includes only investment projects with both Economic Rates of Returns (ERRs) and Revised Economic Rates of Returns (RERRs) and excludes those in the following sectors that do not traditionally calculate rates of return: education, finance, multi-sector, population, health & nutrition, public sector management, and social protection.
Source: Operations Evaluation Department (2003, Table 13).

sizeable economic returns. Three decades ago, Paul Mosley observed that:

> The microeconomic data from evaluations are encouraging: all donors who calculated *ex-post* rates of return on their projects reveal a large preponderance of successful projects. The World Bank, the largest development agency, reports average *ex-post* rates of return of over 10 per cent in every continent and every sector over the 20 year period 1961-81. (Mosley 1986, 22)

More contemporary micro evidence does not shatter the image of relatively high economic returns. On the contrary, the returns cited by Mosley in the mid 1980s are still representative in the late 1990s and early 2000s. As Table 1 documents, median economic rates of return on infrastructure projects are quite respectable; ranging from 10 to 29 per cent, with the overall median being 19 per cent. Moreover, the World Bank's Independent Evaluation Group (IEG) has documented that even though the computation and reporting of economic rates of return has gone out of fashion since the early 2000s, the returns on World Bank projects have not decreased. If anything, they have increased over time (IEG 2010).

Against this background a natural next step is to compare macro estimates of the economic rate of return on aid investments to these micro estimates. To get such macro estimates we follow an approach also used extensively in studies of the productivity of public capital.[1] The approach builds on a set of assumptions, most of which are familiar from the growth accounting literature (Solow 1957). First, we adopt an aggregate production function, exhibiting constant returns to rival factors of production: physical and human capital. Second, we assume that factor shares reflect the marginal productivity of individual factors of production. Third, we assume aid inflows stimulate the build-up of physical capital. On this basis we derive an equation that allows us to identify the marginal product of aid capital.

[1] See Bom and Ligthart (2014) for a survey and meta-analysis of the public investment productivity literature and Calderón, Moral-Benito and Servén (2015) for a recent time series study focusing on the productivity of infrastructure investment.

From an econometric perspective a number of difficulties arise. In contrast to studies of the productivity of public capital that use measures of public and private physical capital we cannot compute a measure of 'aid capital' by cumulating past aid flows. Thus, we cannot estimate the output elasticity of aid capital from the production function. Instead we estimate the average marginal productivity of aid investments directly. Furthermore, (i) the marginal productivity of all inputs vary over time and across countries such that all production function coefficients are essentially random variables; (ii) total factor productivity is unavoidably left in the residuals, and is likely to be correlated with both the regressors and the random coefficients; and (iii) both domestic investments and aid inflows are endogenous. We are, therefore, forced to examine our data using a number of different estimators, all of which deal explicitly with the endogeneity of all regressors. We try to take account of both the random coefficients and the endogeneity by utilizing the panel structure of our data to generate internal instruments. We believe this is preferable to a (seemingly futile) hunt for external instruments.

Our principal finding is remarkably robust: overall the average marginal productivity of aid capital, which is the average *gross* rate of return on foreign aid, appears to be close to 20 per cent. This finding conforms well with the micro returns cited above and it is clearly in agreement with a marginal return on public capital of about 16 per cent in the short run and up to 40 per cent in the long run (see Bom and Ligthart 2014). Just as for public investment, the marginal productivity of aid investment may well be high in countries with concurrent low marginal productivity of private capital, and this is the reason why we claim that Caseli and Feyrer's computation of overall marginal returns on capital from national accounts data has very limited information about the productivity of aid flows.

Our finding of a large and economically significant economic rate of return to aid investments may appear to be in contradiction with the standard aid effectiveness literature in which a positive impact of aid on growth has until recently been debated.[2] However, macro studies of aid effectiveness have typically run (panel) growth regressions where foreign aid is added to a list of other controls, known as the "Barro-regression" approach. The estimated impact of aid on growth will in these regressions depend on both elasticities of the production function as well as on preference parameters (Barro and Sala-i-Martin 1992). As a result, the estimated coefficients from the standard aid effectiveness literature are not directly comparable to economic rates of return on investments in the sense of the latter being the marginal productivity of capital.

In comparison, the present study does not attempt to address the question of whether aid, as such, increases GDP per capita in the long run. We are interested in the marginal productivity of aid financed investments in their own right–just as other parameters of macro production functions are of interest in their own right. This distinction is important. For example, it may be the case that aid inflows crowds out, say, domestic investments in physical capital. In this case the *net* result from aid transfers could be a zero productivity impact albeit 'aid investments' themselves are productive. Of course, it could also be the case that aid investments stimulate domestic investment efforts or foreign direct investments.[3] Either way, in order to obtain estimates for the return on aid investments we condition on other production inputs. Consequently, it is not possible to assess such claims directly. In this respect the present paper

[2]Extensive overviews of the aid effectiveness literature are given in Dalgaard et al. (2004); Roodman (2007); Arndt et al. (2010) and Temple (2010). The most recent literature is covered in Arndt et al. (2015).

[3]See Selaya and Sunesen (2012) for an analysis of the relationship between foreign aid and foreign direct investment, Rajan and Subramanian (2011) for study of of aid and Dutch Disease and Svensson (2000) for a model of aid and rent-seeking.

differs fundamentally in scope from the existing literature on aid effectiveness.

The paper proceeds as follows. Section 2 develops a framework suitable for estimating the aggregate return to foreign aid investments and Section 3 presents our estimation strategy. Our empirical results are given in Section 4 while Section 5 provides concluding remarks. Technical details are given in appendices.

2 Growth accounting with two types of physical capital

Assume output in a country is produced using a Cobb-Douglas technology

$$Y(t) = A(t)K(t)^{\alpha_k}H(t)^{\alpha_l}, \qquad \alpha_k + \alpha_l = 1 \tag{1}$$

where A represents total factor productivity, H is human capital, while K is a composite index of physical capital.[4] Following the empirical growth literature (Hall and Jones 1999; Bils and Klenow 2000) we model human capital by

$$H(t) = e^{\psi u(t)}L(t) \tag{2}$$

where L is the (raw) labour force and u is years of schooling. The parameter ψ has the interpretation of a Mincerian return to schooling.

For physical capital we aggregate two forms of capital by a constant elasticity of substitution (CES) index

$$K(t) = (\pi(K^d(t))^\eta + (1-\pi)(K^f(t))^\eta)^{\frac{1}{\eta}} \tag{3}$$

where K^d is "domestically generated physical capital" (or "domestic capital" for short), and K^f is aid-financed capital equipment – or simply "aid capital".[5] Denote the marginal contribution of each type of capital by

$$\frac{\partial K(t)}{\partial K^d(t)} = \pi \left(\frac{K^d(t)}{K(t)}\right)^\eta \equiv \gamma(t) \tag{4}$$

$$\frac{\partial K(t)}{\partial K^f(t)} = (1-\pi) \left(\frac{K^f(t)}{K(t)}\right)^\eta \equiv (1-\gamma(t)) \tag{5}$$

In theory there is good reason to believe that the two types of investment efforts may have different impacts on economic activity ($\eta \neq 1$). For example, a large fraction of total aid flows comes in the shape of investments in infrastructure. From this perspective, foreign aid investments may have an economic return above private (equipment) investments. On the other hand, if the government and donors are less effective at identifying productive investment projects than the private agents, the impact of aid capital on output may be considerably smaller than that of domestic capital. Moreover, one could easily imagine scenarios where aid capital and domestic capital are either complements or substitutes in generating the aggregate total stock of productive capital K.

[4]The use of a Cobb-Douglas production technology is solely for expositional convenience. In Appendix A we derive the growth accounting equation using a general neo-classical production technology.

[5]Needless to say, in practice it is difficult to dichotomize "domestically generated inputs", and "aid financed inputs" based on national accounts data. We return to this issue below. For now we will simply assume that this distinction is feasible.

Inserting equation (3) into the production function (1), differentiating the resulting equation with respect to time and using the hat-notation for growth rates (for example $\hat{Y}(t) = \dot{Y}(t)/Y(t)$) yields

$$\hat{Y}(t) = \hat{A}(t) + \alpha_k \gamma(t)\hat{K}^d(t) + \alpha_k(1-\gamma(t))\hat{K}^f(t) + \alpha_l \hat{H}(t) \tag{6}$$

Further, suppose capital is accumulated according to

$$\dot{K}^i(t) = I^i(t) - \delta^i K^i(t), \quad i = d, f \tag{7}$$

where $I^i(t), i = d, f$ represents the flow of investments based on domestic savings and foreign aid, respectively, and ^{i} are depreciation rates. Equation (7) can be restated to yield

$$\hat{K}^i(t) = \frac{Y(t)}{K^i(t)} \frac{I^i(t)}{Y(t)} - \delta^i, \quad i = d, f$$

Substituting this expression into equation (6), and noting that, from equation (2), $\hat{H}(t) = \psi \dot{u}(t) + n(t)$, where $\dot{u} = \partial u(t)/\partial t$ is the change over time in schooling and n is the growth rate of the labour force, leaves us with

$$\hat{Y}(t) = \rho^d(t)\frac{I^d(t)}{Y(t)} + \rho^f(t)\frac{I^f(t)}{Y(t)} + \alpha_l \psi \dot{u}(t) + \alpha_l n(t) + \hat{A}(t) - \alpha_k(\gamma(t)\delta^d + (1-\gamma(t))\delta^f) \tag{8}$$

where

$$\rho^d(t) \equiv \alpha_k \gamma(t)\frac{Y(t)}{K^d(t)}, \quad \rho^f(t) \equiv \alpha_k(1-\gamma(t))\frac{Y(t)}{K^f(t)}$$

Accordingly, $\rho^i(t)$ is the marginal productivity of each type of capital and, as such, it has the interpretation of gross aggregate returns on the two types of capital.[6] Hence, from an accounting perspective, the contribution of aid capital to output growth is simply the aid-investment to output ratio multiplied by the relevant economic return.

3 Econometric issues

Even if, as we assume, the growth accounting (8) holds for all countries nothing guarantees equal returns to investments across countries and time. So fundamentally the econometric objective is to identify the (population) average values of $\rho^d(t)$ and $\rho^f(t)$ across time and countries. In this section we discuss some of the issues related to the estimation of these average aggregate returns.

3.1 An observable growth accounting equation

First, observable measures for domestic investment and aid investment must be defined. As not all aid is used for investment it is not possible to extract primary data from any database. Yet, the sum of the two types of investment is known as it equals gross capital formation

$$I(t) = I^d(t) + I^f(t) \tag{9}$$

[6] Capital's share of total income in this economy is $(\rho^d(t)K^d(t) + \rho^f(t)K^f(t))/Y(t) = \alpha_k\gamma(t) + \alpha_k(1-\gamma(t)) = \alpha_k$.

In order to identify the two investment components we assume that aid investments are linearly related to the foreign aid inflows, $F(t)$

$$\frac{I^f(t)}{Y(t)} = \beta \frac{F(t)}{Y(t)} + \phi(t), \qquad 0 < \beta \leq 1 \tag{10}$$

where $\phi(t)$ is a country and time specific term, which we model as a random component. The important assumption in (10) is that the (unconditionally) expected marginal investment ratio out of aid flows is constant while the average ratio may vary across countries and time.[7]

Combining (10) and the adding-up constraint (9), domestically funded investments can be found as the residual

$$\frac{I^d(t)}{Y(t)} = \frac{I(t) - \beta F(t)}{Y(t)} - \phi(t) \tag{11}$$

and inserting equations (10) and (11) into (8) yields

$$\hat{Y}(t) = \rho^d(t)\left[\frac{I(t) - \beta F(t)}{Y(t)} - \phi(t)\right] + \rho^f(t)\left[\frac{\beta F(t)}{Y(t)} + \phi(t)\right] + \alpha_l \psi \dot{u}(t) + \alpha_l n(t) + \hat{A}(t) - \alpha_k(\gamma\delta^f + (1-\gamma)\delta^d) \tag{12}$$

Finally, using a convex combination of the returns to domestic investment and aid investment, $\rho^c(t) = (1-\beta)\rho^d(t) + \beta\rho^f(t)$ we can rearrange (12) to an observable growth accounting equation

$$\hat{Y}(t) = \rho^d(t)\left[\frac{I(t) - F(t)}{Y(t)}\right] + \rho^c(t)\left[\frac{F(t)}{Y(t)}\right] + \alpha_l \psi \dot{u}(t) + \alpha_l n(t) + \hat{A}(t) - \alpha_k(\gamma\delta^f + (1-\gamma)\delta^d) + \phi(t)\tfrac{1}{\beta}(\rho^c(t) - \rho^d(t)) \tag{13}$$

In this equation there is a measurement error, $\phi(t)\frac{1}{\beta}(\rho^c(t) - \rho^d(t))$, which is zero if the returns on the two types of investments are equal, but in general it is correlated both with the returns and the regressors.

When estimating the parameters of (13) neither $\rho^f(t)$ nor β are identified. However, for given values of $\rho^d(t), \rho^c(t)$, and β the return on aid investments is

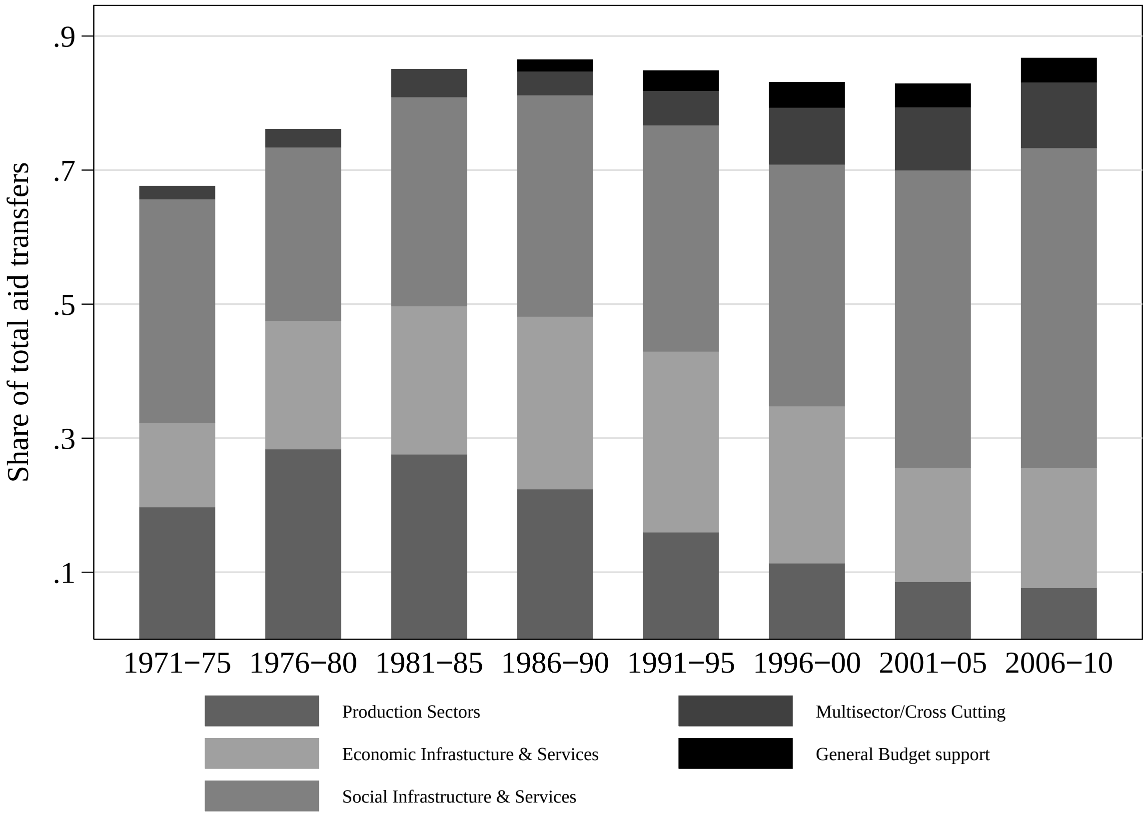
$$\rho^f(t) = \rho^d(t) + \frac{1}{\beta}(\rho^c(t) - \rho^d(t)) \tag{14}$$

It is difficult to pinpoint an exact value for β. A rough guide can be obtained by looking at the allocation of Official Development Assistance (ODA) commitments across sectors. In Figure 1 we show the allocation of aid transfers form 1971 to 2010. As seen, about 70per cent of the aid transfers are allocated to either "Production sectors", "Economic infrastructure & services" or "Social infrastructure & services".[8] While not all aid to these sectors is investment we believe that a marginal aid investment share of at least 0.5 and probably closer to 0.7 is a reasonable assumption.

[7]It is worth noticing that $\phi(t)$ is not (only) related to the standard notion of fungibility of foreign aid. Donor preferences towards specific projects or programmes also play a prominent role in determining the size of $\phi(t)$.

[8]In the computation of the shares we have omitted food aid, humanitarian aid and action related to debt.

Figure 1: Sectoral composition of ODA transfers 1971-2010, five year averages



Note: The omitted sector is Unallocated Aid.
Source: OECD online database (http://www.oecd.org/dac/stats/).

3.2 The regression model

Because the returns to investments in physical and human capital are expected to vary both over time and across countries we specify the observable growth accounting equation (13) as a random coefficients model and seek to estimate the unconditional mean of the coefficients. Thus, let the returns and the growth rate of total factor productivity be random vectors with a constant mean and covariance matrix. Then the growth accounting equation can be written as a structural regression model such that for any randomly drawn country we may think of (13) as a conditional expectation

$$\mathrm{E}(y_{it}|\mathbf{x}_{it},\mu_{it},\rho_{it},\phi_{it}) = \mathbf{x}_{it}\rho_{it} + \mu_{it} + \phi_{it}\iota\rho_{it} \tag{15}$$

where y_{it} is the growth rate of output in country i at time t, $\mathbf{x}_{it} = [\{(I_i(t) - F_i(t))/Y_i(t)\}, (F_i(t)/Y_i(t)), \dot{u}_i(t), n_i(t)]$ is the vector of regressors and $\rho_{it}' = [\rho^d(t), \rho^c(t), \alpha_l\psi, \alpha_l]$ is the corresponding vector of returns and parameters while μ_{it} captures the growth rate of total factor productivity (TFP) and the depreciation rates, suitably scaled. Finally, ϕ_{it} is the aid investment measurement error and $\iota = \frac{1}{\beta}[-1,1,0,0]$.

Following the panel data literature we assume the random coefficients have an additive error-component structure (see for example Hsiao 2014, chapter 6). The covariances between the relevant components of ρ_{it}, μ_{it}, and ϕ_{it} are unrestricted, as these are obviously related, being the random components of returns and TFP growth. Further, the coefficients are in all likelihood correlated with the regressors. Hence, (15) describes a correlated random coefficient model.

This model has been studied by Heckman and Vytlacil (1998), Wooldridge (1997, 2003 and 2005) and Murtazashvili and Wooldridge (2008). In the present analysis we mainly follow the instrumental variable approach set out in Wooldridge (2003, 2005) although we do not assume strict exogeneity of the instruments. The explicit model formulation is given in Appendix B. In this section we only describe the most salient model features.

The error component structure allows for the possibility that some countries consistently have higher returns and TFP growth rates than others and that such countries invest more (or less) of the aid inflow compared to other countries. Furthermore, a common variation across countries captures world wide business cycle movements in the returns. Finally, a common time varying measurement error can reflect changes in donor policies regarding aid modalities, such as changes from projects (investment in physical capital) to programmes (with higher fractions of expenditures on government consumption such as road maintenance or teacher salaries).

In Appendix B we show how the random coefficient model (15) can be recast as a linear regression model

$$y_{it} = \mathbf{x}_{it}\rho + c + v_{it} \tag{16}$$

Where ρ is the (unconditional) mean return, c is a constant, with no structural interpretation, and v_{it} is a composite error term with $\mathrm{E}(v_{it}) = 0$. In this model ρ can be consistently estimated if we can find a set of instruments, $\mathbf{z}_{it}$, such that $\mathrm{E}(\mathbf{z}_{it}v_{it}) = 0$ (and for which the usual rank condition hold). Subsequently, using (14), consistent estimates of the average of ρ^f can be obtained for given values of β.

Because of the additive error component structure various panel data transformations of the regressors may be valid instruments. The usefulness of each transformation depends on the specific assumptions about the covariance between the returns and the regressors. Below we consider each variance component in turn.

First, suppose the association between the random components and the regressors is solely via a common variation over time, for example through common business cycles. In this situation, let $\mathbf{z}_{it}$ be the residuals from a regression of $\mathbf{x}_{it}$ on time dummies. As the regression on time dummies eliminate time specific components from $\mathbf{x}_{it}$, $\mathbf{z}_{it}$ is a valid instrument. By the partialling out interpretation of the projection on time dummies it follows that a standard pooled ordinary least squares regression of (16) augmented by time dummies is a consistent estimator of the average returns given the assumption.

Second, assume the association between the random components and the regressors is only via co-movements across countries, possibly due to differences in time invariant productivity determinants, including institutions, culture and geography. This case is considered by Wooldridge (2005) who shows that the standard fixed effects estimator is consistent. The point to note is that regression of $\mathbf{x}_{it}$ on country dummies (or using first differences of the data) removes the source of association between the regressors and the regression error.

Third, a contemporaneous association between the idiosyncratic random components and the regressors may be present as high returns should induce investments. If this is the only association, a standard instrumental variable regression using the lagged regressors as instruments ($\mathbf{z}_{it} = \mathbf{x}_{it-s},\ s > 0$) is consistent, given the assumption that the idiosyncratic components of the returns are uncorrelated over time.

Finally, if all covariance components are allowed to be non-zero each of the estimators given above is inconsistent but we can combine the transformations to obtain valid instruments. Specifically, lagged differences of the regressors, conditional on time dummies, are valid instruments. Needless to say, while this transformation produces valid instruments the instruments may be weak. We address this issue in the empirical section.

4 Empirical results

We use data for 104 countries covering the 50 years 1961-2010. The aid data is from the OECD online database.[9] We use net ODA from which we subtract technical assistance, food aid, humanitarian aid and debt relief to remove aid that is clearly not invested in physical capital. Education is measured by total years of schooling in the population above 25 years of age (tyr25) from the updated Barro-Lee data set (Barro and Lee 2013).[10]

As there has been much controversy over national accounts data we estimate the growth accounting model using two different data sources. First, in Section 4.1 we use data on gross domestic product (GDP), investment (gross capital formation), and the labour force from the World Development Indicators (WDI) online database.[11] Second, in section 4.2 we use data from Penn World Tables 8.1 (PWT) (see, Feenstra, Inklaar and Timmer 2015).[12]

In both analyses the annual data is divided into 10 non-overlapping, five-year epochs of averages. The countries in the two samples are given in Appendix C. Because of data transformations and the use of lags in instrumental variable regressions, our regressions start with the period covering 1971-75 using the two periods in the 1960s to form first differences and instruments.

4.1 Results for WDI data

Using the World Development Indicators data base we divide the annual aid transfers and the gross capital formation data, which are both in current US$, by recipient country GDP in current US$ (NY.NKT.GDP.CD in WDI notation). Thus, the ratios are formed from current, national prices. Subsequently we subtract the aid-to-GDP ratio from the investment ratio to get the first regressor, while using the aid-to-GDP ratio as the second regressor. In about 2.6per cent of the sample (18 observations) the aid transfer is larger than total investment. For these observations we set domestic investment to zero and foreign investment equal to total investment. Clearly, this is not true in any country, however, it appears to be the least arbitrary choice and by this restriction all observations adhere to the adding-up constraint (9), also when $\beta = 1$. Further, in 45per cent of the sample we have no data on labour force growth. For these observations we use the growth rate of the population 15-64 years of age.

Table 2 reports the regression results. The dependent variable in the regressions is the average annual growth of GDP (constant 2005 US$; NY.NKT.GDP.KD), using log-changes as an approximation of the annual growth rates. As shown in Section 3.1 the average returns and other structural parameters can be consistently estimated from the parameter estimates in the

[9]http://www.oecd.org/dac/stats/. Assessed May 2015.
[10]http://www.barrolee.com.
[11]http://databank.worldbank.org. Assessed May 2015.
[12]http://www.rug.nl/research/ggdc/data/pwt/. Assessed May 2015

linear regression. The average return to domestic investment, ρ^d, is the coefficient upon investment less aid, while the average elasticity of output with respect to (raw) labour input, α_l, is the coefficient upon the growth rate of the labour force. The average return to education, ψ, is estimated as the ratio of the coefficient upon education to the coefficient upon labour force growth. Finally, using equation (14), the return to aid investments can be derived for given values of the expected marginal share of aid invested, β.

The columns in Table 2 gives the estimated parameters based on a range of different estimators. Regression (1) is an ordinary least squares (OLS) regression with no additional controls while Regression (2) includes time dummies. As described in section 3.2, if the association between the regressors and the random components is *only* through the common variation over time, Regression (2) is a consistent estimator. Regression (3) is a fixed effect (FE) regression with both time and country fixed factors, such that it is consistent in the presence of correlated common random variation over time and correlated time invariant random components.

Regressions (4)-(7) are instrumental variable regressions. Regression (4) is two stage least squares (TSLS), (5) is limited information maximum likelihood with Fuller's correction (Fuller), (6) is the continuously updated generalized methods of moments estimator by Hansen et al. (1996) (CUGMM) and, finally, regression (7) is Arellano and Bover's (1995) generalized methods of moments estimator with sequential moment restrictions (SeqGMM). We use two lags of the differences of investments and aid flows, while the differences of the annual average changes in education and the average labour force growth rate are included using lags 0 and 1. Hence, the model has eight instruments for the four endogenous regressors. We use internal instruments to avoid a seemingly futile search for external data that are correlated with aid and investment ratios but not with the random components of the returns to these investments. Hence, in selecting instruments we balance the number of instruments against the loss of observations over time. By using one lag of the first differences we have a regression sample starting in 1971 for the IV-regressions. The instrument exclusion restrictions are tested using the Sargan-Hansen test. The *p*-values of these test statistics are reported in Table 2 (given as "Over id" in the Table) and, as seen, we cannot reject the hypotheses of valid instruments in the four regressions.

Validity of the instruments does not ensure unbiased estimators as the instruments may be weak. In testing for weak instruments we follow Stock and Yogo (2005). Thus, weakness of the instruments is defined in terms of the squared bias of the IV-estimator relative to the squared bias of the least squares estimator. Using a 10per cent relative bias the 95%-critical value of the weak instrument test is 9.79 for the TSLS estimator, while the critical value is 6.08 for a 20 per cent relative bias and 4.66 for a 30 per cent relative error (see Table B in Appendix C). Hence, we cannot reject the null of weak instruments for the now conventional choice of a 10 per cent relative bias, but we reject the hypothesis for a 30 per cent bias for the TSLS estimator.[13] As illustrated in Stock et al. (2002), robust alternatives to the TSLS estimator with weak instruments are the Fuller estimator and the CUGMM estimator. Hence, we also report results for these estimators to illustrate that weak instruments do not appear to be distorting the results given that the TSLS, Fuller and CUGMM estimates are very close.[14]

[13] See Stock, Wright and Yogo (2002) for a discussion of weak instrument problems and solutions and Kleibergen and Paap (2006) for the robust test statistic.

[14] The critical values for the weak instrument size-test are currently not known for the Fuller and CUGMM estimators in models with more than 2 endogenous regressors. Hence, we cannot report these critical values, but analytical results show that they are smaller than the critical values for the TSLS estimator, and decreasing in the number of instruments.

Table 2: Estimates of average growth accounting parameters 1971-2010

	(1) OLS	(2) OLS	(3) FE	(4) TSLS	(5) Fuller	(6) CUGMM	(7) SeqGMM
ρ^d	13.55	13.67	13.34	14.77	14.77	15.88	16.42
	(2.73)	(2.64)	(3.44)	(5.52)	(5.50)	(5.38)	(5.81)
ρ^c	15.26	17.08	26.73	19.12	19.11	18.35	22.30
	(4.32)	(4.13)	(5.96)	(9.24)	(9.22)	(9.00)	(8.45)
α_l	0.62	0.64	0.83	0.47	0.47	0.37	0.81
	(0.18)	(0.17)	(0.22)	(0.24)	(0.24)	(0.23)	(0.31)
ψ	3.77	5.99	1.33	12.30	12.29	17.33	11.61
	(3.29)	(3.43)	(2.41)	(10.16)	(10.16)	(14.83)	(5.75)
Equal returns	0.62	0.33	0.02	0.53	0.53	0.71	0.25
Over id				0.85	0.85	0.86	0.37
Weak id				5.31	5.31	5.31	
Countries	103	103	103	94	94	94	103
Observations	673	673	673	506	506	506	608
Estimated return to foreign aid investments (using equation (14))							
$\rho^f(\beta = 0.5)$	16.97	20.50	40.11	23.47	23.44	20.82	28.19
	(7.34)	(7.15)	(11.10)	(15.33)	(15.29)	(14.79)	(12.69)
$\rho^f(\beta = 0.7)$	15.99	18.55	32.46	20.99	20.96	19.41	24.82
	(5.55)	(5.36)	(8.08)	(11.74)	(11.72)	(11.38)	(10.17)
$\rho^f(\beta = 0.9)$	15.45	17.46	28.22	19.61	19.59	18.62	22.96
	(4.63)	(4.44)	(6.49)	(9.87)	(9.85)	(9.59)	(8.88)

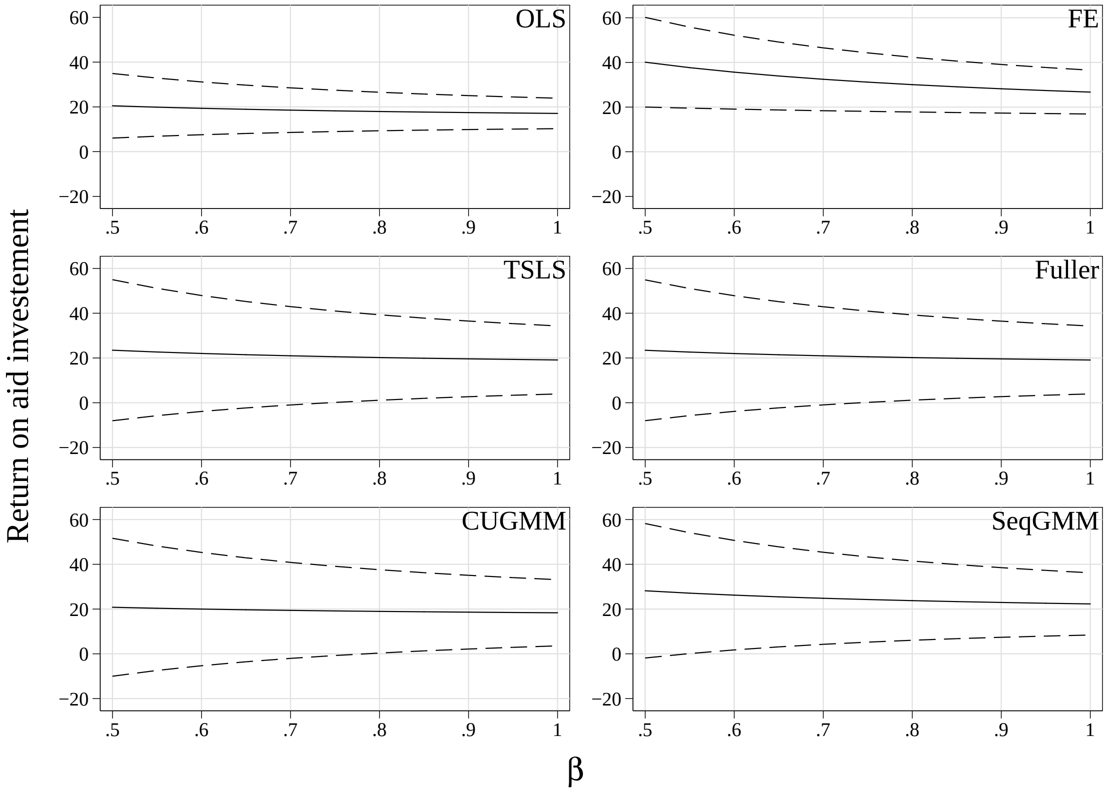
Note: Country level heteroskedasticity and autocorrelation robust standard errors in parentheses. The instruments in regressions (4), (5), (6) and (7) are differences of investments and aid flows, lagged once and twice, and differences of changes in education and labour force growth, contemporaneous and lagged once. For the over identification tests the p-values of the test statistics are reported. For the weak identification tests the Kleibergen-Paap F test is reported. See Kleibergen and Paap (2006) and Baum et al. (2007).
Source: Authors' calculations.

While the Fuller estimator is (partially) robust to weak instruments, it is not efficient in the presence of conditional heteroskedasticity in the errors. This is the reason why we also use the CUGMM estimator and as the efficient counterpart to the TSLS estimator, we include the panel GMM estimator with sequential moment restrictions.[15] To balance asymptotic efficiency and finite sample bias in the sequential moment GMM regression we restrict the model to include at most two lags of the instruments in all periods.

Turning to the results, the estimated average return to domestic investment (ρ^d) is remarkably constant across estimators. The three least squares based regressions that ignore contemporaneous correlation between investments and returns (Regressions (1)-(3)) result in point estimates of the return on domestic investment around 13 per cent whereas the IV-based estimators have slightly higher point estimates (15-16%). The estimates of the composite average return (ρ^c) show a different pattern as we find a marked upward shift in the estimates once time-invariant,

[15]The moment restrictions are given from the condition: $\mathrm{E}(v_{it}|\Delta\ddot{\mathbf{x}}_{it-s}) = 0$ for $s > 0$, where $\Delta\ddot{\mathbf{x}}_{it}$ is the the first difference of the regressors, conditional on common time factors, see Appendix B. For the annual average change in education and the labour force growth rate we use $s \geq 0$.

Figure 2: Estimates of the return to aid investments as a function of the marginal propensity to invest out of aid flows with 90% point-wise confidence bands



Source: Authors' calculations.

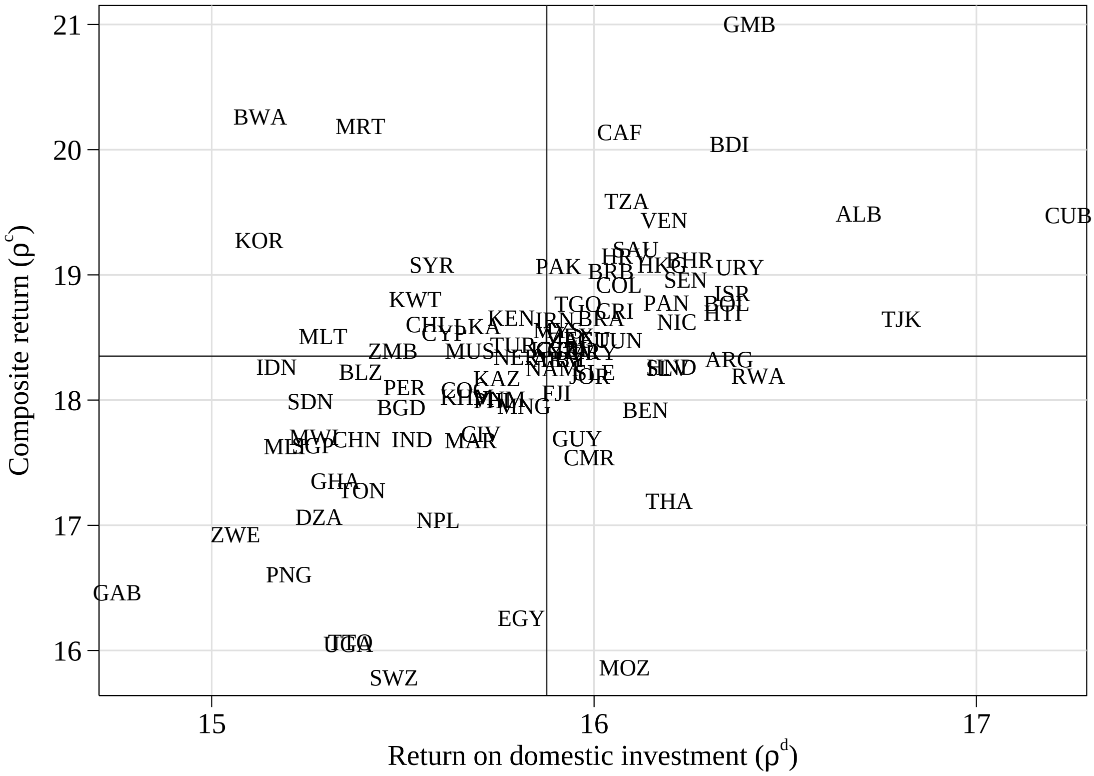
country specific factors are controlled for. In Regressions (1) and (2) the average composite return is about 16%, while the point estimates are 18-22 per cent in the IV-regressions and even 27 per cent in the fixed effects regression.

The impact of education and labour force growth also vary considerably with the choice of estimator. Although the standard rule of thumb from the national accounts statistics puts α_l around 2/3, Bernanke and Gürkaynak (2001) illustrates a wide variation across countries and that values as low as 0.5 and as high as 0.75 are quite common. In our regressions the estimates, varying from 0.37 to 0.81, are not unreasonable given the sampling variation. Likewise, we find the estimates of the returns to education to vary substantially by estimator. Still, estimates of an average return to schooling of 12-17 per cent per additional year of education in the IV-regressions (4)-(6) are well in accordance with other estimates.

Overall, we find the IV-regressions to be well-specified in a statistical sense of not having obvious flaws and also in an economic sense of having parameters that corresponds well to findings elsewhere, using other methods and models. Therefore, we focus on these regressions in our assessment of the return on aid investments.

In the bottom part of Table 2 we report estimates of the return for three values of β (0.5; 0.7; 0.9) and in Figure 2 we plot the estimated returns to aid investments for values of β from 0.5 to 1 based on the parameter estimates in Regressions (2)-(7) in Table 2. The return to aid investments is estimated using equation (14) and the standard errors are estimated using the Delta method. As the point estimate of the composite return (ρ^c) is larger than the point estimate

Figure 3: Estimates of the return to domestic investments and the composite return when countries are omitted from the sample one-by-one



Note: The country marker indicates the estimated return when the country is omitted from the sample. The horizontal and vertical lines show the full sample estimates. Leshoto (21.4;24.8) is omitted from the plot.
Source: Authors' calculations.

of the return on domestic capital (ρ^d) in all regressions in Table 2 it follows that the return to aid investment is inversely related to the marginal investment share. However, Figure 2 clearly illustrates that the estimated difference between the return on domestic investment and the composite investment is so small that the precise marginal investment share is of lesser importance compared to the sampling uncertainty and the variation across countries and time (possibly except for the results of the fixed effects regression, where we get a substantial difference between the returns). As such, regardless of the specific value of β and specific choice of IV-estimator we would not be able to reject a hypothesis that the gross average return to aid investments is 20%.

Given that the two return parameters are means of random variables, which we expect vary across countries it is of interest to gauge the influence of the individual countries for the estimated means. We illustrate the importance of country selection by omitting each country from the regression sample one-by-one. Figure 3 is a cross-plot of the point estimates of the return to domestic investment against the point estimates of the composite return when each of the 94 countries is omitted in a CUGMM regression. The country code in the plot indicates the point estimates when the country is omitted. We therefore get the importance of each country in the full sample estimate by the distance to the full sample result, indicated by the intersection of the two lines in the plot. For example, if Gabon is not in the sample we get point estimates just above 14 per cent and 16 per cent for the return on domestic aid and the composite return, respectively. Hence, inclusion of Gabon in the sample leads to higher point estimates than exclusion (all else equal). The highest pair is obtained by omitting Lesotho (21;25, not shown in the plot). The full sample estimates appear robust to exclusion of individual countries and the estimated composite return exceeds the estimated return on domestic investment in all sub-samples while the difference between the two returns is quite constant, as also seen from the Figure.

In sum, from the IV-regressions in Table 2, Figure 2 and the sample perturbations in Figure 3 we find it reasonable to assert that the average aggregate return on aid investment is in close to 20 per cent. This corresponds well to the median returns for World Bank projects reported in Table 1 and to the marginal productivity of public capital reported in Bom and Ligthart (2014).

4.2 Results for PWT data

Several recent studies have shown how cross-country regression results may depend crucially on data sources for the national accounts statistics.[16] Therefore, we report and discuss regression results based on data from Penn World Tables 8.1 (PWT) in this section. Specifically, we use the growth rate of GDP based on the constant price series `rgdpna`, as suggested in Feenstra, Inklaar and Timmer (2015) while we look at two different investment ratios. First we form investment and aid ratios in international \$. Thus, aid and investments are converted to international \$ using the PPP GDP deflator (`pl_gdpo`) and subsequently divided by the corresponding GDP measure in international prices (`cgdpo`). These ratios should correspond to the investment and aid ratios computed using the WDI data. Second, aid and investment are deflated by the PPP investment deflator (`pl_i`) and subsequently divided by GDP (`cgdpo`). The latter measures are denoted real ratios.[17] Hsieh and Klenow (2007) point out that the two different investment ratios have substantially different cross-country patterns.

In Table 3 the first four regressions use nominal investment and aid ratios while the last four regressions are based on real ratios. As for the WDI data, a few countries have periods in which the aid flow exceed gross capital formation (21 observations). Again, we set domestic investment to zero and aid investment equal to total investment in these instances. For comparison with the results for the WDI data we report results for the fixed effects, the Fuller, the CUGMM and the sequential moment GMM estimator.

An important change in the results is that the instruments appear to be critically weak in the regressions using nominal ratios, while the real investment ratios are marginally better.[18] Still, the differences in the estimates using WDI or PWT data and nominal investment and aid ratios are very small relative to the estimated dispersion.

For the IV-regressions using real investment ratios (Regressions (6)-(8)) we get lower returns compared to using nominal investment ratios. This is of interest because Caselli and Feyrer (2007) illustrate how the difference in the two investment ratios has important implications for the marginal return on reproducible capital across countries when these are calibrated using (PWT) national accounts data. Generally, the marginal product of capital decreases for the

[16] A recent prominent example is Barron, Miguel and Satyanath (2014).

[17] The correlation between the WDI and PWT nominal investment ratios is 0.86 while it is 0.96 for the aid ratios. By conversion to real ratios the correlations drop to 0.60 and 0.88 for the investment and aid ratio, respectively.

[18] The critical values for the weak instrument test are the same as for the WDI-based TSLS regressions, given in Table B.

Table 3: Growth accounting estimates using GDP and investment data from PWT 8.1

	Nominal investment ratio				Real investment ratio			
	(1) FE	(2) Fuller	(3) CUGMM	(4) SeqGMM	(5) FE	(6) Fuller	(7) CUGMM	(8) SeqGMM
ρ^d	15.05	14.33	13.52	18.75	9.27	12.91	8.50	11.26
	(3.37)	(5.57)	(4.78)	(4.84)	(2.92)	(8.16)	(7.14)	(4.87)
ρ^c	31.90	20.45	15.59	19.90	24.45	21.51	17.83	19.13
	(7.43)	(10.85)	(9.16)	(9.44)	(8.21)	(14.99)	(13.73)	(10.82)
α_l	0.87	1.06	0.68	0.80	0.94	1.12	0.50	0.89
	(0.34)	(0.49)	(0.42)	(0.31)	(0.35)	(0.52)	(0.43)	(0.32)
ψ	3.24	5.38	7.79	6.29	4.05	7.63	13.89	7.95
	(2.86)	(3.29)	(5.78)	(3.75)	(2.67)	(3.61)	(11.28)	(3.73)
Equal returns	0.01	0.54	0.80	0.87	0.03	0.47	0.39	0.37
Over id		0.52	0.54	0.60		0.65	0.67	0.26
Weak id		2.98	2.98			4.65	4.65	
Countries	95	93	93	95	95	93	93	95
Observations	694	557	557	611	694	557	557	611
Estimated return to foreign aid investments (using equation (14))								
$\rho^f(\beta = 0.5)$	48.75	26.58	17.66	21.05	39.62	30.11	27.16	27.01
	(13.08)	(20.00)	(16.80)	(16.16)	(15.01)	(25.87)	(23.69)	(19.12)
$\rho^f(\beta = 0.7)$	39.12	23.08	16.47	20.40	30.95	25.19	21.83	22.51
	(9.80)	(14.65)	(12.33)	(12.24)	(11.09)	(19.50)	(17.87)	(14.30)
$\rho^f(\beta = 0.9)$	33.77	21.13	15.82	20.03	26.13	22.46	18.86	20.01
	(8.03)	(11.81)	(9.96)	(10.15)	(8.95)	(16.12)	(14.77)	(11.70)

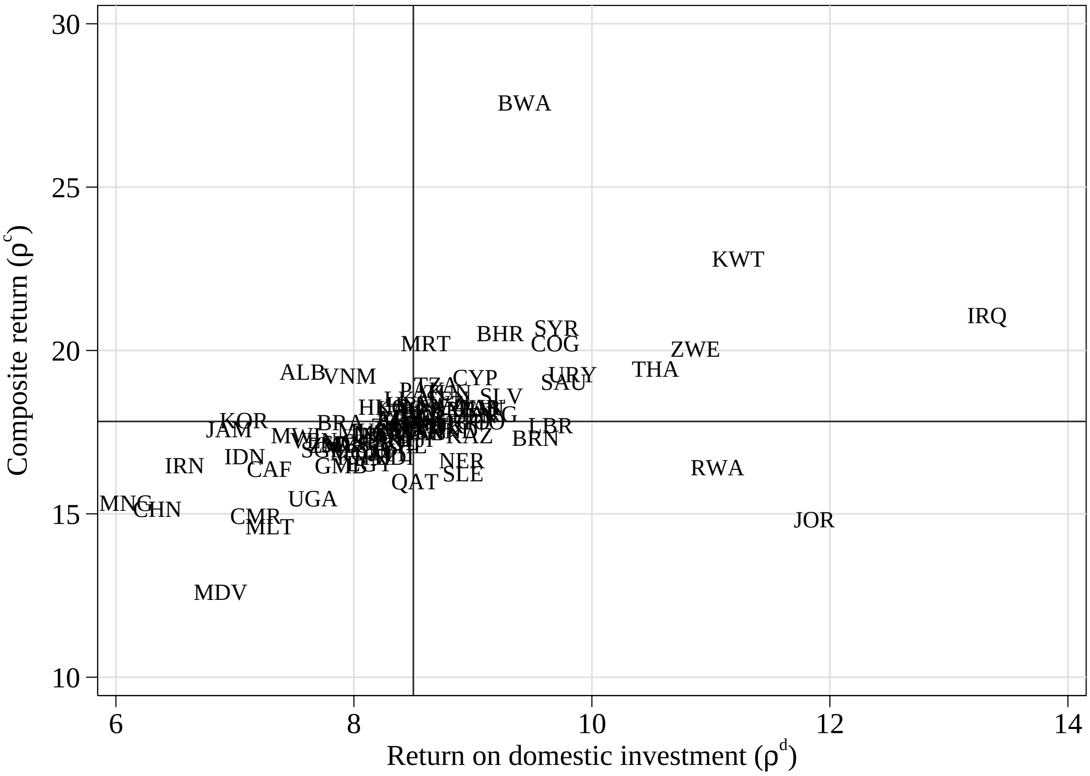
Note: Country level heteroskedasticity and autocorrelation robust standard errors in parentheses. The instruments in regressions (2)-(4), and (6)-(8) are differences of investments and aid flows, lagged once and twice, and differences of changes in education and labour force growth, contemporaneous and lagged once. For the over identification tests the p-values of the test statistics are reported. For the weak identification tests the Kleibergen-Paap F test is reported. See Kleibergen and Paap (2006) and Baum et al. (2007).
Source: Authors' calculations.

poorest countries when using real investment ratios instead of nominal investment ratios. Our regressions show the same pattern (estimator by estimator), however, the return on aid investments is still substantial, and substantially larger than the 8-9 per cent return on reproducible capital reported in Caselli and Feyrer (2007).

We have also estimated the model omitting countries one-by-one for the PWT data using the real investment ratios. The result is given in Figure 4. For this data we find a larger dispersion in the estimated returns and omission of several countries, such as in particular Botswana, Kuwait, Iraq and Jordan, generate low return estimates. Looking beyond the extremes, 90 per cent of the estimates of the return on domestic investments are between 7 per cent and 11 per cent while the corresponding bound is 15-20 per cent for the composite return. Moreover, we again find that the composite return exceeds the domestic return in all sub-samples with a median, and mean, difference of 9 percentage points, such that the average return on aid investments is very likely to exceed the average return on domestic investments, regardless of the specific value of the marginal propensity to invest out of the aid flows.

Overall, the regression results using national accounts data from both WDI and PWT illus-

Figure 4: Estimates of the return to domestic investments and the composite return when countries are omitted from the sample one-by-one: Using PWT 8.1 data and real investment ratios



Note: The country marker indicates the estimated return when the country is omitted from the sample. The horizontal and vertical lines show the full sample estimates.
Source: Authors' calculations.

trate that the size of the estimated average gross return on domestic and aid investments are respectable and the latter return is probably larger than the former and close to 20 per cent.

5 Conclusion

Over the past 50 years researchers have scrutinized the effectiveness of aid as a tool to increase economic growth and reduce poverty in the third world. Even so, much is yet to be learned on this issue. We believe the present paper contributes to this research agenda by providing an estimate of the *average* gross real rate of return on aid financed investments in physical capital. Given the recent revival in aid funding of large infrastructure projects, illustrated by the establishment of the Asian Infrastructure Investment Bank, our results are also relevant for policy makers.

We identify the return on aid investments on the basis of a standard growth accounting framework. The advantage of this line of attack is the comparative simplicity of the structural model. Another advantage is the theoretical separation of production function parameters from preferences parameters, which is not feasible in the Barro-type growth regressions that are the normally applied in cross-country aid effectiveness studies. This separation is what allows us to identify the gross real rates of return.

The transparency of the economic model comes at the cost of added econometric complexity as returns are likely to vary across countries and time. Moreover, the returns are in all likelihood correlated with the unobserved growth rates in total factor productivity and, hence, the investment ratios. A feasible, and fairly simple, solution to the econometric problem lies in formulating the structural model as a correlated random coefficient model in which the average returns can be identified and consistently estimated using instrumental variable estimators, assuming the random components of the returns are additively decomposable along cross-country panel dimensions.

Based on two different sources for the national accounts data (World Development Indicators and Penn World Tables 8.1), our principal finding is that the average aggregate gross rate of return on aid investments is close to 20 per cent. Intriguingly, this is in accord with median World Bank project level estimates. Moreover, aid investments are, on average, at least as productive as domestically funded investments in physical capital. Thus, our results do not seem to support theories of aid ineffectiveness that rely on inefficient aid investment allocation.

If aid investments are centred on projects for which international private capital flows cannot generate equal returns across developed and developing countries and government borrowing on the international commercial bank market is restricted, the result need not contradict the finding of roughly equal (total) aggregate marginal productivity of investment in reproducible physical capital across countries. The marginal productivity of aid investment may well be high in countries with concurrent low marginal productivity of private capital, illustrating that computing overall marginal returns on capital from national accounts data has very limited information about the productivity of aid investments.

Our approach fundamentally recognizes that the return on both domestic and aid financed investments are likely to vary considerably across countries and time. Exploring this heterogeneity is likely to be a revealing avenue for future research. For example, previous research have suggested that factors like the policy environment, the institutional setting in general, or perhaps geographic circumstances, matter for the aggregate marginal productivity of aid financed investments. Our approach is capable of turning these propositions into testable hypotheses.

References

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

Arndt, C., S. Jones, and F. Tarp (2010). Aid, Growth, and Development: Have We Come Full Circle? *Journal of Globalization and Development* 1(2): Article 5.

Arndt, C., S. Jones, and F. Tarp (2015). What Is the Aggregate Economic Rate of Return to Foreign Aid? *World Bank Economic Review* 29(2). doi:10.1093/wber/lhv033.

Barro, R.J. and J.-W. Lee (2013). A new data set of educational attainment in the world, 1950-2010. *Journal of Development Economics*, 104: 184-198.

Barro, R.J. and X. Sala-i-Martin (1992). Convergence. *Journal of Political Economy,* 100: 223-51.

Barron, M., E. Miguel and S. Satyanath (2014). Economic shocks and democratization in Africa, *Political Science Research and Methods*, 2: 33-47.

Baum, C. F., M. E. Schaffer, and S. Stillman (2007). ivreg2: Stata module for extended instrumental variables/2SLS, GMM and AC/HAC, LIML, and k-class regression. Boston College Department of Economics, Statistical Software Components S425401.

Bernanke, B.S. and R.S. Gürkaynak (2001). Is growth exogenous? Taking Mankiw, Romer and Weil seriously. *NBER Macroeconomics Annual* 16: 11-57.

Bils, M. and P.J. Klenow (2000). Does schooling cause growth? *American Economic Review*, 90: 1160-83.

Bom, P.R.D. and J. E. Ligthart (2014). What have we learned from three decades of research on the productivity of public capital?, *Journal of Economic Surveys*, 28(5): 889-916.

Calderón, C., E. Moral-Benito, and L. Servén (2015). Is infrastructure capital productive? A dynamic heterogenous approach, *Journal of Applied Econometrics*, 30: 177-198.

Caselli, F. and J. Feyrer (2007). The marginal product of capital. *Quarterly Journal of Economics*, 122: 535-68.

Dalgaard, C.-J., H. Hansen and F. Tarp (2004). On the empirics of foreign aid and growth. *Economic Journal*, 114: F191-F216.

Feenstra, R.C., R. Inklaar and M.P. Timmer (2015). The next generation of the Penn World Table, *American Economic Review*, 105(10): 3150-3182

Hall, R.E. and C.I. Jones (1999). Why do some countries produce so much more output per worker than others?, *Quarterly Journal of Economics*, 114(1): 83-116.

Hansen, L.P., J. Heaton and A. Yaron (1996). Finite-sample properties of some alternative GMM estimators, *Journal of Business and Economic Statistics*, 14: 262-280.

Heckman, J.J. and E. Vytlacil (1998). Instrumental variables methods for the correlated random coefficient model. *Journal of Human Resources*, 33: 974-87.

Hsiao, C. (2014). *Analysis of Panel Data*, 3rd. edition. Cambridge: Cambridge University Press.

Hsieh, C.-T. and P.J. Klenow (2007). Relative prices and relative prosperity, *American Economic Review*, 97(3): 562-585.

IEG (Independent Evaluation Group) (2010). Cost-benefit analysis in World Bank projects, Washington DC: The World Bank.

Jones, L.E. and R.E. Manuelli (1990). A convex model of equilibrium growth: theory and policy implications. *Journal of Political Economy*, 98: 1008-38.

Kleibergen, F. and R. Paap (2006). Generalized reduced rank tests using the singular value decomposition. *Journal of Econometrics*, 133: 97-126.

Lucas, R.E. Jr. (1990). Why doesn't capital flow from rich to poor countries?, *American Economic Review*, 80(2): 92-96.

Mosley, P. (1986). Aid-effectiveness: the micro-macro paradox. *Institute of Development Studies Bulletin*, 17: 22-7.

Murtazashvili, I. and J.M. Wooldridge (2008). Fixed effects instrumental variables estimation in correlated random coefficient panel data models. *Journal of Econometrics*, 142: 539-552.

Operations Evaluation Department (2003). *Annual Review of Development Effectiveness*, Statistical Annex, The World Bank.

Rajan, R.G. and A. Subramanian (2011). Aid, Dutch disease, and manufacturing growth. *Journal of Development Economics*, 94: 106-118.

Roodman, D. (2007). The Anarchy of Numbers: Aid, development, and cross-country empirics. *World Bank Economic Review*, 21: 255-77.

Selaya, P. and E.R. Sunesen (2012). Does foreign aid increase foreign direct investment?, *World Development*, 40(11): 2155-2176.

Solow, R. (1957). Technical change and the aggregate production function, *Review of Economics and Statistics*, 39: 312-20.

Stock, J.H., J.H. Wright and M. Yogo (2002). A survey of weak instruments and weak identification in generalized method of moments. *Journal of Business and Economic Statistics*, 20: 518-29.

Stock, J.H. and M. Yogo (2005). Testing for weak instruments in linear iv regressions, In D.W.K. Andrews and J.H. Stock (eds.), *Identification and Inference for Econometric Models: Essays in Honor of Thomas Rothenberg*, Cambridge: Cambridge University Press.

Svensson, J. (2000). Foreign aid and rent-seeking, *Journal of International Economics*, 51: 437-461.

Temple, J.R.W. (2010). Aid and conditionality, In D. Rodrik and M. Rosenzweig (eds.), *Handbook of Development Economics*, Chapter 67, Volume 5, pp. 4415-4523. Elsevier.

Wooldridge, J.M. (1997). On two stage least squares estimation of the average treatment effects in a random coefficient model. *Economics Letters*, 56: 129-33.

Wooldridge, J.M. (2003). Further results on instrumental variables estimation of average treatment effects in the correlated random coefficient model. *Economics Letters*, 79: 185-91.

Wooldridge, J.M. (2005). Fixed effects and related estimators for correlated random coefficient and treatment effect panel data models. *Review of Economics and Statistics*, 87: 385-390.

A Growth decomposition with a more general production function

Instead of the Cobb-Douglas production function we may assume output is produced using a more general neoclassical production technology

$$Y(t) = A(t)F(K(t), H(t)) \tag{17}$$

where, again, A represents total factor productivity, H human capital, while K is the composite index of physical capital. Now, instead of the CES-aggregate let

$$K(t) \equiv G(K^d(t), K^f(t)) \tag{18}$$

in which aid capital is a non-essential production input

$$G(K^d(t), 0) = \pi K^d(t), \qquad \pi > 0$$

We impose constant returns to scale in the three (rival) inputs taken together

$$\lambda Y(t) = A(t)F(G(\lambda K^d(t), \lambda K^f(t)), \lambda H(t))$$

The assumptions imply that in the event the stock of aid capital is zero, constant returns to human input and (domestic) capital input prevail. As a result, regardless of whether aid is present or not, the production technology is consistent with the national accounts identity which states that total capital and labour compensation equals total value added.

We do not impose any conditions on the relative size of the partial derivatives, G_1' and G_2', nor on the cross-partial G_{12}''. In general the latter could be either positive, negative or zero (perfect substitutes).

Inserting (18) into the production function (17) and differentiating the resulting equation with respect to time results in a more general expression than the one in Section 2

$$\hat{Y}(t) = \hat{A}(t) + \frac{F_K G_1' K^d(t)}{F(\cdot)} \hat{K}^d(t) + \frac{F_K G_2' K^f(t)}{F(\cdot)} \hat{K}^f(t) + (1 - \alpha(t))\hat{H}(t) \tag{19}$$

where $1 - \alpha(t) = 1 - (A(t)F_K)G/Y(t) = (A(t)F_H)H(t)/Y(t)$ represents the share of labour in value added.

Inserting the law of motion for capital into (19) then yields

$$\begin{aligned}\hat{Y}(t) = \left[A(t)F_K G_1'\right] \frac{I^d(t)}{Y(t)} + \left[A(t)F_K G_2'\right] \frac{I^f(t)}{Y(t)} + (1 - \alpha(t))\hat{H}(t) \\ + \hat{A}(t) - \{\alpha(t)[\gamma(t)\delta^d(t) + (1 - \gamma(t))\delta^f(t))\}\end{aligned} \tag{20}$$

where we have used that $Y(t) = A(t)F(\cdot)$ and defined $\gamma(t) = G_1' K^d(t)/G$.

In this setting the return parameters becomes

$$\rho^d(t) \equiv \frac{\partial Y(t)}{\partial K^d(t)} = A(t)F_K G_1', \qquad \rho^f(t) \equiv \frac{\partial Y(t)}{\partial K^f(t)} = A(t)F_K G_2'$$

and this leaves the following more general expression for the growth rate of output

$$\begin{aligned}\hat{Y}(t) = \rho^d(t)\frac{I^d(t)}{Y(t)} + \rho^f(t)\frac{I^f(t)}{Y(t)} + (1 - \alpha(t))\hat{H}(t) \\ + \hat{A}(t) - \{\alpha(t)[\gamma(t)\delta^d(t) + (1 - \gamma(t))\delta^f(t))\}\end{aligned} \tag{21}$$

The expression simplifies to equation (8) with the specific choice of production technology in Section 2.

B The correlated random coefficient model with two-way error component structure

B.1 Model formulation

We assume the random coefficients in equation (15) have an additive error-component structure, which we specify as

$$\rho_{it} = \rho + \Theta_{it} = \rho + \Upsilon_i + \Lambda_t + \xi_{it} \tag{22}$$
$$\mu_{it} = \mu + \theta_{it}^{\mu} = \mu + \upsilon_i^{\mu} + \lambda_t^{\mu} + \varepsilon_{it}^{\mu} \tag{23}$$
$$\phi_{it} = \phi + \theta_{it}^{\phi} = \phi + \upsilon_i^{\phi} + \lambda_t^{\phi} + \varepsilon_{it}^{\phi} \tag{24}$$

where ρ, μ, and ϕ are the unconditional expectations, $\mathrm{E}(\rho_{it}) = \rho$, $\mathrm{E}(\mu_{it}) = \mu$, $\mathrm{E}(\phi_{it}) = \phi$, and the error components $\Upsilon_i, \Lambda_t, \xi_{it}, \upsilon_i^{\mu}, \lambda_t^{\mu}, \varepsilon_{it}^{\mu}, \upsilon_i^{\phi}, \lambda_t^{\phi}$, and ε_{it}^{ϕ} are mean zero (vector) random variables with a standard panel data error-components covariance structure

$$\begin{aligned}
&\mathrm{E}(\Upsilon_i \Upsilon_j') = 0, && \mathrm{E}(\upsilon_i^{\mu} \upsilon_j^{\mu}) = 0, \quad \mathrm{E}(\upsilon_i^{\phi} \upsilon_j^{\phi}) = 0 && \text{for } i \neq j \\
&\mathrm{E}(\Lambda_t \Lambda_s') = 0, && \mathrm{E}(\lambda_t^{\mu} \lambda_s^{\mu}) = 0, \quad \mathrm{E}(\lambda_t^{\phi} \lambda_s^{\phi}) = 0 && \text{for } t \neq s \\
&\mathrm{E}(\xi_{it} \xi_{js}') = 0, && \mathrm{E}(\varepsilon_{it}^{\mu} \varepsilon_{js}^{\mu}) = 0, \quad \mathrm{E}(\varepsilon_{it}^{\phi} \varepsilon_{js}^{\phi}) = 0 && \text{for } i \neq j, \text{ and } t \neq s
\end{aligned}$$

The covariances between the relevant components of ρ_{it}, μ_{it}, and ϕ_{it}, say, Υ_i, υ_i^{μ}, and υ_i^{ϕ} are left unrestricted. For simplicity, we assume the covariance structure is constant

$$\mathrm{E}(\Theta_{it} \theta_{js}^{\phi}) = \mathrm{E}(\Upsilon_i \upsilon_j^{\phi}) + \mathrm{E}(\Lambda_t \lambda_s^{\phi}) + \mathrm{E}(\xi_{it} \varepsilon_{js}^{\phi}) = \Sigma_{\Upsilon\upsilon} \delta_{ij} + \Sigma_{\Lambda\lambda} \delta_{ts} + \Sigma_{\xi\varepsilon} \delta_{ij} \delta_{ts} \tag{25}$$

for all i, j and t, s where δ_{ab} is Kronecker's delta.

Turning to the regressors, we consider a fairly general linear error-component specification

$$\mathbf{x}_{it} = f_i + g_t + r_{it} \tag{26}$$

where the country and time specific components, r_{it}, are assumed to follow a general covariance stationary process independent of the common effects, g_t, and the time invariant effects f_i.[19]

Given the specification of the coefficients and the regressors, the possible association between the returns and the regressors can be specified

$$\mathrm{E}(\Theta_{it} \mathbf{x}_{js}) = \mathrm{E}(\Upsilon_i f_j) + \mathrm{E}(\Lambda_t g_s) + \mathrm{E}(\xi_{it} r_{js}) = \Sigma_{\Upsilon f} \delta_{ij} + \Sigma_{\Lambda g} \delta_{ts} + \Sigma_{\xi r} \delta_{ij} \delta_{ts} \tag{27}$$

Each of the covariance-components, $\Sigma_{\Upsilon f}, \Sigma_{\Lambda g}$ and, $\Sigma_{\xi r}$ may be non-zero, in which case the model is a correlated random coefficient model.

Inserting equations (22)-(24) in (15) and using the error form of the model it may be formulated as

$$y_{it} = \mathbf{x}_{it} \rho + c + v_{it} \tag{28}$$
$$c = \mu + \sigma_{\mathbf{x}\Theta} + \sigma_{\phi\Theta} + \phi \iota \rho, \tag{29}$$
$$v_{it} = (\mathbf{x}_{it} \Theta_{it} - \sigma_{\mathbf{x}\Theta}) + (\theta_{it}^{\phi} \iota \Theta_{it} - \sigma_{\phi\Theta}) + \theta_{it}^{\mu} + \theta_{it}^{\phi} \iota \rho + \phi \iota \Theta_{it} + e_{it} \tag{30}$$

[19] Assuming independence of the three components is stronger than needed. However, as we require more than mean independence in the following the assumption is convenient.

where

$$\sigma_{\mathbf{x}\Theta} = \mathrm{E}(\mathbf{x}_{it}\Theta_{it}) \equiv \mathrm{Tr}(\Sigma_{\Upsilon f} + \Sigma_{\Lambda g} + \Sigma_{\xi r})$$
$$\sigma_{\phi\Theta} = \mathrm{E}(\theta_{it}^{\phi}\iota\Theta_{it}) \equiv \mathrm{Tr}[(\Sigma_{\Upsilon\upsilon} + \Sigma_{\Lambda\lambda} + \Sigma_{\xi\varepsilon})\iota]$$

and e_{it} is the expectation error derived from the structural model (15).

In this system $\mathrm{E}(v_{it}) = 0$ (by construction) and, hence, ρ can be consistently estimated if there exist a set of instruments, $\mathbf{z}_{it}$, such that $\mathrm{E}(v_{it}|\mathbf{z}_{it}) = 0$. In addition, equation (29) makes clear that the intercept in the equation is of little interest, being a sum of mean and covariance components.

B.2 Identification

Wooldridge (2003) consideres estimation of population average effects in the correlated random coefficients model in a cross-section and shows that standard instrumental variables estimators are consistent under fairly weak conditions. In the following we state these assumptions and show how standard panel data transformations of the regressors yield valid instruments under reasonable assumptions.

It follows from (28) and (30) that a vector of instrumental variables, $\mathbf{z}_{it}$, is valid if it satisfies the following exogeneity conditions:[20]

$$\mathrm{E}(y_{it}|\mathbf{x}_{it}, \mu_{it}, \rho_{it}, \phi_{it}, \mathbf{z}_{it}) = \mathrm{E}(y_{it}|\mathbf{x}_{it}, \mu_{it}\rho_{it}, \phi_{it}). \tag{A1}$$
$$\mathrm{E}(\mu_{it}|\mathbf{z}_{it}) = \mathrm{E}(\mu_{it}) = \mu, \quad \mathrm{E}(\rho_{it}|\mathbf{z}_{it}) = \mathrm{E}(\rho_{it}) = \rho \tag{A2}$$
$$\mathrm{E}(\Theta_{it}\mathbf{x}_{it}|\mathbf{z}_{it}) = \mathrm{E}(\Theta_{it}\mathbf{x}_{it}) \equiv \Sigma_{\Upsilon f} + \Sigma_{\Lambda g} + \Sigma_{\xi r} \tag{A3}$$
$$\mathrm{E}(\theta_{it}^{\phi}|\mathbf{z}_{it}) = 0 \tag{A4}$$
$$\mathrm{E}(\Theta_{it}\theta_{it}^{\phi}|\mathbf{z}_{it}) = \mathrm{E}(\Theta_{it}\theta_{it}^{\phi}) \equiv \Sigma_{\Upsilon\upsilon} + \Sigma_{\Lambda\lambda} + \Sigma_{\xi\varepsilon} \tag{A5}$$

Assumption (A1) is the usual order condition. Assumption (A2) adds the condition that the instrumental variables are ignorable for the random coefficients, while assumption (A3) specifies that the instruments are also ignorable for the covariance between the regressors and the random coefficients. Assumption (A3) is stronger than needed, as the necessary condition is that the trace of the conditional covariance matrix shold not depend on (functions of) the instrument. However, it is hard to imagine cases in which this distinction is important.[21] Finally, it should be noted that independence of the coefficients and the instruments is a sufficient condition for (A2) and (A3).

Because of the measurement error in aid investments, two additional conditions are added. The first of these, (A4), is the standard ignorability condition. The second, (A5), adds a conditional independence assumptions for the covariance between the random return coefficients and the measurement error.

Assumptions (A2), (A4) and (A5) can be gathered by considering the vector of random components in the model, say, $\chi_{it} = [\Theta_{it}', \theta_{it}^{\mu}, \theta_{it}^{\phi})]'$. A sufficient condition, encompassing the

[20] Assumptions (A1)-(A3) are given in Wooldridge (2003).

[21] Wooldridge (2003) specifies the independence condition for each of the diagonal elements in the conditional covariance matrix. Needless to say, this intermediate assumption is also sufficient but not necessary.

three conditions above, is second order independence of χ_{it} with respect to the instruments: $\mathrm{E}(\chi_{it}|\mathbf{z}_{it}) = 0$ and $\mathrm{Var}(\chi_{it}|\mathbf{z}_{it}) = \mathrm{Var}(\chi_{it})$.

From (A1)-(A5) it follows that the conditional expectation of the regression error given the instruments is zero, $\mathrm{E}(v_{it}|\mathbf{z}_{it}) = 0$. $\mathrm{E}(\theta^{\mu}_{it}|\mathbf{z}_{it}) = 0$ and $\mathrm{E}(\phi\iota\Theta_{it}|\mathbf{z}_{it}) = 0$ by (A2), $\mathrm{E}(\theta^{\phi}_{it}\iota\rho|\mathbf{z}_{it}) = 0$ by (A4), while $\mathrm{E}(\mathbf{x}_{it}\Theta_{it}|\mathbf{z}_{it}) = \sigma_{\mathbf{x}\Theta}$ and $\mathrm{E}(\phi_{it}\iota\Theta_{it}|\mathbf{z}_{it}) = \sigma_{\phi\Theta}$ follows from (A3) and (A5). Therefore $\mathbf{z}_{it}$ is a valid instrument in equation (28) and given the existence of such an instrument and the usual rank condition, we can consistently estimate the average returns, ρ.

B.3 Estimation

The moment conditions implied by the assumptions are $\mathrm{E}(\mathbf{z}_{it}v_{it})$, which in the present setting can be made explicit as five different components: (i) $\mathrm{E}(\mathbf{z}'_{it}\theta^{\mu}_{it}) = 0$, (ii) $\mathrm{E}(\mathbf{z}'_{it}\Theta_{it}) = 0$, (iii) $\mathrm{E}(\mathbf{z}'_{it}\theta^{\phi}_{it}) = 0$, (iv) $\mathrm{E}(\mathbf{z}'_{it}(\mathbf{x}_{it}\Theta_{it} - \sigma_{\mathbf{x}\Theta})) = 0$, and (v) $\mathrm{E}(\mathbf{z}'_{it}(\phi_{it}\iota\Theta_{it} - \sigma_{\phi\Theta})) = 0$. In Section 3 we explore, informally, various data transformations generating instruments which support the moment conditions under different assumptions about the covariance structure. Here we relate these transformations to the parametric set-up given in this Appendix.

1. When the association between the random components and the regressors is soley through a common variation across time, the covariance is related to g_t and the error components Λ_t, λ^{μ}_t or λ^{ϕ}_t. Further, we have the two products, $g_t\Lambda_t$ and $\lambda^{\phi}_t\iota\Lambda_t$ that may also be correlated with g_t. But regressing $\mathbf{x}_t$ on time dummies removes g_t (in the limit) and leaves the residuals $\mathbf{z}_{it} = f_i + r_{it}$. These residuals are uncorrelated with v_{it} but clearly correlated with $\mathbf{x}_{it}$.

2. When the association between the random components and the regressors is only via co-movements across countries we have a symmetric argument relative to above. The specific covariance is between the regressor component f_i and the error components Υ_i, υ^{μ}_i, υ^{ϕ}_i, or the products $f_i\Upsilon_i$, $\upsilon^{\phi}_i\iota\Upsilon_i$. Regressing $\mathbf{x}_{it}$ on country dummies removes f_i and leaves the residuals $\mathbf{z}_{it} = g_t + r_{it}$ (in the limit). These residuals are uncorrelated with any of the relevant error components, but correlated with $\mathbf{x}_{it}$. Another common transformation is to use first differences of the regressors as instruments whereby $\mathbf{z}_{it} = (g_t - g_{t-1}) + (r_t - r_{t-1})$ this instrument is clearly also correlated with the regressors, and it is uncorrelated with the error term under the stated assumptions.

3. When the association is a contemporaneous association between the idiosyncratic random components and the regressors the covariance is between r_{it} and the error components ξ_{it}, ε^{μ}_{it} or ε^{ϕ}_{it} or the composite variables $r_{it}\xi_{it}$ and $\varepsilon_{it}\iota\xi_{it}$. The crucial assuption is that the error components are uncorrelated over time such that r_{it-s}, $(s > 0)$ is not correlated with any of the terms. This means that lagged observations of the regressors $\mathbf{x}_{it-s} = f_i + g_{t-s} + r_{it-s}$ are valid instruments that are obviously correlated with the regressors under the stated assumptions.

4. Finally, when all covariance components are allowed to be non-zero we can combine the three transformations to obtain valid instruments. Specifically, let $\ddot{\mathbf{x}}_{it}$ be the residuals from a regression of $\mathbf{x}_{it}$ on time dummies, then the lagged differences of the regressors, conditional on time dummies are valid instruments $\mathbf{z}_{it} = \Delta\ddot{\mathbf{x}}_{it-s} = \Delta r_{it-s}$, $s > 0$. In this case, the relevance of the instrument hinges on an assumption of (sufficient) autocorrelation in r_{it}.

As seen the parameters of interest in (28), ρ, can be estimated using methods of moments estimators such as TSLS or more general GMM estimators. In particular, the sequential moment GMM estimator suggested by Arellano and Bover (1995) in which the regressors are predetermined and have constant correlation with the individual effects is an obvious choice of estimator in the present setting. Other GMM estimators, such as the continously updated GMM estimator by Hansen et al. (1996) using lags of the first difference transformation of the variables are of course also valid.

C The sample of countries

Table A: The sample of countries

Country	WDI	PWT	Country	WDI	PWT	Country	WDI	PWT
Afghanistan	2	0	Guyana	8	0	Pakistan	8	8
Albania	5	5	Haiti	3	0	Panama	7	7
Algeria	8	0	Honduras	8	8	Papua New Guinea	7	0
Argentina	8	8	Hong Kong	6	6	Paraguay	4	4
Armenia	4	4	India	8	8	Peru	8	8
Bahrain	5	6	Indonesia	8	8	Philippines	8	8
Bangladesh	8	8	Iran, Islamic Rep.	8	8	Qatar	1	1
Barbados	8	8	Iraq	2	2	Rwanda	8	8
Belize	7	7	Israel	6	6	Saudi Arabia	8	8
Benin	8	8	Jamaica	0	8	Senegal	8	8
Bolivia	8	8	Jordan	7	7	Sierra Leone	7	7
Botswana	8	8	Kazakhstan	4	4	Singapore	5	5
Brazil	8	8	Kenya	8	8	Slovenia	2	3
Brunei	2	2	Korea, Rep.	6	6	South Africa	4	4
Burundi	8	8	Kuwait	1	5	Sri Lanka	8	8
Cambodia	4	4	Kyrgyz Republic	4	4	Sudan	7	7
Cameroon	8	8	Lao PDR	5	5	Swaziland	8	8
Central African Republic	8	8	Lesotho	8	8	Syrian Arab Republic	8	8
Chile	8	8	Liberia	3	3	Tajikistan	4	4
China	7	7	Libya	3	0	Tanzania	5	5
Colombia	8	8	Malawi	8	8	Thailand	8	8
Congo, Rep.	8	8	Malaysia	8	8	Togo	8	8
Costa Rica	8	8	Maldives	1	3	Tonga	6	0
Cote d'Ivoire	8	8	Mali	8	8	Trinidad and Tobago	8	8
Croatia	3	4	Malta	7	7	Tunisia	8	8
Cuba	8	0	Mauritania	8	8	Turkey	8	8
Cyprus	5	6	Mauritius	7	7	Uganda	6	8
Ecuador	8	8	Mexico	8	8	Ukraine	2	2
Egypt, Arab Rep.	8	8	Mongolia	6	6	Uruguay	8	8
El Salvador	8	8	Morocco	8	8	Venezuela, RB	8	8
Fiji	8	8	Mozambique	6	7	Vietnam	5	5
Gabon	8	8	Namibia	6	6	Yemen, Rep.	4	5
Gambia, The	8	8	Nepal	8	8	Zambia	6	6
Ghana	8	8	Nicaragua	8	0	Zimbabwe	8	8
Guatemala	8	8	Niger	8	8			

Note: The WDI and PWT columns indicate the number of observations each country has in the OLS regressions using the WDI and PWT data, respectively.
Source: Authors' listing.

Table B: Critical values for the weak instrument test based on relative squared bias of TSLS relative to OLS. The model has 4 endogenous regressors and 8 instruments.

Maximal relative bias	10%	20%	30%
95% critical value	9.79	6.08	4.66
90% critical value	9.02	5.49	4.15

Source: Authors' calculations based on Gauss program written by M. Yogo.