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ABSTRACT

The Lucas Paradox observes that capital flows predominantly to relatively rich countries, contradicting the neoclassical prediction that it should flow to poorer capital-scarce countries. Alfaro, Kalemli-Ozcan, and Volosovych (2008) (AKV) argue that cross-country variation in institutional quality can fully explain the Paradox, contending that if institutional quality is included in regression models explaining international capital inflows, a country's level of economic development is no longer statistically significant. We replicate AKV's results using their cross-sectional IFS capital flow data. Motivated by the importance of conducting inference in statistically adequate models, we focus on misspecification testing of alternative functional forms of their empirical model of capital flows. We show that their resolution of the Paradox relies on inference in a misspecified model. In models that do not fail basic misspecification tests, even though institutional quality is a significant determinant of capital inflows, a country's level of economic development also remains a significant predictor. The same conclusions are reached using an extended dataset covering more recent IFS international capital flow data, first-differenced capital stock data and additional controls.

Keywords
Lucas Paradox; capital flows; foreign direct investment; institutions; misspecification testing

JEL Classification
F21; F34; F41; E02; C52

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I. Introduction

Neoclassical theory predicts that capital, if allowed to move freely, should flow from relatively capital-abundant, low-return countries to capital-scarce, high-return countries, until rates of return are equalized (Solow 1956). This reallocation of capital from richer to poorer countries is regarded as doubly beneficial because capital recipients have a higher marginal productivity of capital than capital lenders (assuming diminishing returns to capital and common technology) and because it facilitates convergence of cross-country levels of per capita income (Barro, Mankiw, and Sala-i-Martin 1995; Gourinchas and Jeanne 2006). In reality, however, flows of capital from rich to poor countries are much lower than predicted by standard neoclassical theory. Observing this inconsistency, Lucas (1990, p.92) posed the question: "Why doesn't capital flow from rich to poor countries?", which became known as the 'Lucas Paradox'. More than a quarter of a century later, despite a substantial number of empirical studies attempting to find a solution to the Paradox, it remains relevant and, arguably, unresolved.

The empirical literature addressing the Lucas Paradox has two main strands. One group of studies aims to refine the measurement of cross-country differences in the marginal product of capital to account for cross-country differences in human capital (Lucas 1990), endowment of natural resources (Caselli and Feyrer 2007), adjustment costs (Chirinko and Mallick 2008), credit market imperfections (Swan 2008) or public vs private capital (Lowe, Papageorgiou, and Perez-Sebastian 2014). In these studies, a resolution of the Lucas Paradox is achieved if the revised estimates of the marginal product of capital are relatively higher in rich, capital-abundant countries.

The second, more extensive, set of studies adopts a reduced-form regression-based approach to analyse the determinants of capital inflows. The determinants typically included can be classified under three broad headings: fundamentals, capital market imperfections/

frictions, and institutions (Clemens and Williamson 2004). Fundamentals include factors that directly influence the ex-ante returns to capital, e.g. human capital, urbanization, migration rates or endowments of natural resources (Lucas 1990; Borensztein, De Gregorio, and Lee 1998; Noorbakhsh, Paloni, and Youssef 2001; Clemens and Williamson 2004). In contrast, capital market imperfections, e.g. barriers to international capital movements and lower levels of financial integration with the world economy (Abiad, Leigh, and Mody 2009; Kalemli-Ozcan et al. 2010; Reinhardt, Ricci, and Tressel 2013), lack of financial development (Forbes 2010; von Hagen and Zhang 2010; Gourinchas and Jeanne 2013) and information asymmetries (Portes and Rey 2005; Hashimoto and Wacker 2016), contribute to a wedge between ex-ante and ex-post returns to capital and could therefore potentially explain the Lucas Paradox. More recently, the quality of institutions, including property rights, expropriation risk, governance, the extent of government corruption and the risk of sovereign default, has been argued to affect political risks and the cost of doing business; this influences the ex-ante returns to capital and hence capital inflows (Wei 2000; Reinhart and Rogoff 2004; Busse and Hefeker 2007; Alfaro, Kalemli-Ozcan, and Volosovych 2008; Asiedu, Jin, and Nandwa 2009; Papaioannou 2009; Buchanan, Le, and Rishi 2012; Lucke and Eichler 2016).

Alfaro, Kalemli-Ozcan, and Volosovych (2008) (AKV), in an influential empirical study claiming to resolve the Lucas Paradox, include an institutional quality index (reflecting property rights and good governance) in a cross-section regression model explaining capital flows. They find that institutional quality is a quantitatively and statistically significant determinant of capital inflows. Moreover, they argue it can fully account for the Paradox, in the sense that the positive and statistically significant relationship between a country’s level of GDP per capita and its capital inflows per capita (i.e. richer countries attracting larger capital flows) disappears if an institutional quality index is included as an explanatory variable in the regression model.

This resolution of the Paradox has been questioned in studies reporting results for cross-sectional regression models in which the addition of institutional quality as a regressor does not fully account for the significant effect of income per capita (Azémar and Desbordes 2013; Snyder 2013; Göktan 2015). The source of much of the conflict between AKV's results and those of their critics centres on the appropriate model specification that is used as a basis for assessment of the statistical significance of the coefficients on income per capita and institutional quality. We contribute to this debate by re-examining AKV's results, using their data. Rather than relying on an *a priori* assumption about the appropriate functional form or selecting models purely on the basis of goodness-of-fit, we use misspecification testing of the validity of the statistical models' assumptions to establish which functional form(s) can secure the reliability of statistical inference. We also explore the sensitivity of the empirical results to changes in model specification and the effect of outliers in the data. We find that AKV's resolution of the Paradox is highly dependent on their choice of a misspecified linear-log functional form, a result consistent with the critique by Azémar and Desbordes (2013).

The rest of the article is organized as follows. In Section II, we replicate the empirical analysis of AKV (2008). Diagnostic testing of the underlying statistical assumptions required for valid inference reveals that the linear-log functional form adopted by AKV is clearly misspecified. In Section III we consider different functional forms for the fitted models. When the empirical model is respecified and the effects of data outliers examined, institutional quality, although quantitatively and statistically significant in explaining capital inflows, is no longer able to fully explain the Lucas Paradox; the quantitative and statistical significance of income per capita is not removed. In Section IV, we examine whether institutional quality can resolve the Lucas Paradox using an extended dataset that includes additional variables; we reach the same conclusion. In Section V, we re-examine the instrumental variables (IV) estimates reported by AKV and consider similar estimates for the extended dataset; results are again sensitive to choice of functional form and weak identification is a concern. Section VI concludes.

II. Replicating AKV's results and misspecification testing

AKV (2008) investigate the determinants of capital flows for a cross-sectional sample of 98 countries, using aggregate capital inflow data averaged over the period 1970 to 2000. They adopt a cross-section approach on the grounds that most of the explanatory variables in their model change slowly over time; in particular, their main variable of interest, an index of institutional quality, shows relatively little time-series variation over the span of the available data. Their use of averaged cross-section data is also motivated by a desire to capture long-run effects associated with the different explanations of the Lucas Paradox.

The basic specification of AKV's empirical model is:

$$F_i = \mu + \alpha \ln Y_i + \beta I_i + \gamma X_i + \varepsilon_i \qquad (1)$$

where F_i, per capita real inflows of direct (FDI) and portfolio equity investment (averaged over the period 1970-2000) in country *i*, is assumed to be a function of initial real GDP per capita (Y), an index of institutional quality (I), other control variables (X), and a stochastic error term (ε). AKV assume the partial relationship between F and Y has a linear-log functional form, as in equation (1), where ln denotes natural logarithms.

In equation (1), a positive and statistically significant coefficient (α) on $\ln Y$ demonstrates the existence of the Lucas Paradox (i.e. richer countries attract larger capital flows). Resolution of the Paradox involves checking whether α becomes statistically insignificant (or reverses in sign) with the addition of any single variable or set of variables.

AKV use data from three different sources to measure capital inflows. Their primary data source is *International Financial Statistics* (IFS) from the International Monetary Fund (IMF). They also examine data compiled by Kraay et al. (2005) and Lane and Milesi-Ferretti

(2007) (LM) that include valuation effects due to capital gains and losses, and/or changes in exchange rates; for these measures, AKV calculate capital inflows as the annual changes in the relevant stocks. In this study, we focus on the original IFS capital flow data that AKV use in their study (but we also use the LM data to examine the robustness of the results for our extended data set in section IV).[1]

The index of institutional quality used by AKV is an aggregate of 11 components taken from Political Risk Services (PRS) Group's International Country Risk Guide (ICRG) (PRS Group 2001) and is measured on a 0-10 scale. For initial real GDP per capita, AKV use the 1970 value of purchasing power parity (PPP) adjusted GDP per capita from the Penn World Table (PWT) 6.1 or, as an alternative, GDP per capita in constant US dollars (deflated by the 1996 US CPI) from *World Development Indicators* (WDI). The additional controls (X_i) include average years of schooling (Barro and Lee 2001) to proxy for levels of human capital, the IMF's (2001) *de jure* measure of legal restrictions on cross-border capital flows to measure capital account restrictions, and a distantness index to measure remoteness and information frictions.[2]

AKV's key result is that cross-country differences in institutional quality can account for the Lucas Paradox; including the institutional quality variable in the regression model explaining capital inflows is sufficient to render the coefficient on log GDP per capita statistically insignificant at conventional significance levels. This is illustrated by comparing columns (1) and (2) in Table 1, which reproduce the coefficient estimates in AKV's Table 3 for their 'whole world' sample of 98 countries; a similar result is obtained for their 81-country 'base' sample, reproduced in Table 1, columns (7) and (8). AKV therefore conclude that differences in institutional quality between rich and poor countries provide a definitive resolution of the Lucas Paradox.

[1] We are grateful to the authors for sharing the IFS data that they use in their study.
[2] Full details of variable definitions and data sources are provided in AKV (2005).

Examination of the properties of AKV's IFS data, however, suggests the choice of a linear-log functional form for the relationship between per capita capital flows and GDP per capita in equation (1) is not ideal. A histogram plot (Figure 1a) reveals that the dependent variable is highly skewed to the right. Also, a plot of the dependent variable against the log of GDP per capita (Figure 1b) displays an obvious pattern of heteroskedasticity in the data. For the validity of inference, the distributional properties of the dependent variable conditional on the explanatory variables, i.e. the error terms, are more important; we therefore focus on testing the key assumptions underlying conventional inference in the regression model, i.e. normality of the error terms, homoskedasticity and correct functional form.

Doornik and Hansen's (2008) test for normality (denoted *Norm*) is based on the skewness and kurtosis of the OLS residuals and is approximately $\chi^2(2)$ distributed under the null of normal errors. Two versions of White's (1980) test for heteroskedasticity are considered: *Hetero* is based on an auxiliary regression of the squared residuals on a constant, the original regressors and their squares, whereas *HeteroX* also includes cross-products of the regressors in the auxiliary regression. Both test statistics are distributed as finite-sample-adjusted F approximations to asymptotic χ^2 distributions under the null of unconditional homoskedasticity. Functional form misspecification (e.g. neglected nonlinearities) is tested using a RESET test that includes squares and cubes of the fitted values of the dependent variable from the original regression as additional regressors; this is denoted *RESET* and is approximately F-distributed under the null that the coefficients on these additional regressors are zero. For ease of interpretation, the tables report p-values for all the diagnostic tests.

The results for these tests in Table 1 for AKV's linear-log functional form (in columns (1), (2), (7) and (8)) provide strong evidence of misspecification, with p-values for all the tests equal to zero to at least two decimal places.

III. Alternative functional forms

Snyder (2013), examining similar IFS data on capital flows per capita, argues that a linear-linear model provides a better fit than a linear-log model, "which may be a contributing factor for why AKV found the coefficient on log GDP insignificant when controlling for institutional quality" (p.288). A linear-linear functional form, as in Table 1, column (3), does give a marginally better fit (i.e. higher R^2) than the corresponding linear-log model in column (2). It also appears to overturn AKV's resolution of the Lucas Paradox, as GDP per capita remains statistically (and quantitatively) significant even if the institutions index is included in the model. However, the diagnostic tests provide equally strong evidence of misspecification of the linear-linear model.

Transforming a highly skewed variable by taking logarithms can often produce a relatively more symmetric distribution, giving less emphasis to the extreme observations, and a more homogenous variance through the range of the variable. Taking logs requires the data to take positive values; the presence of non-positive values in the sample requires either dropping these observations or adding an arbitrary positive constant to ensure that each observation takes a positive value.[3] Alternatively, the inverse hyperbolic sine (IHS) transformation, $\sinh^{-1}(y) = \ln(y + (y^2 + 1)^{0.5})$ can be used. This transformation is monotonic and approximates the conventional log transformation over the positive range but is linear around zero, permitting transformation of zero and negative values, unlike the conventional log transformation; its use therefore entails no reduction in the number of observations (Burbidge, Magee, and Robb 1988; Busse and Hefeker 2007).

We find an IHS-transformed version of AKV's dependent variable is more symmetric and more closely approximates a normal distribution (Figure 2a). Also, a plot of the IHS-

[3] Although the latter method is widely used, especially in modelling of trade flows, it has the drawback that the point estimates of the coefficients can be sensitive to the choice of the added constant (Flowerdew and Aitkin 1982; Burger, van Oort, and Linders 2009).

transformed capital flows per capita against the log of GDP per capita (Figure 2b) does not display an obvious pattern of heteroskedasticity in the data, although there appear to be outliers (i.e. observations that are substantially different in some respect from other observations in the sample). Fitting the model, with the IHS-transformed dependent variable (which, in Table 1, we label the 'IHS' model), i.e.

$$\sinh^{-1}(F_i) = \mu + \alpha \ln Y_i + \beta I_i + \gamma X_i + \varepsilon_i \tag{2}$$

we find that inclusion of the institutions index, although reducing the point estimate of α from 1.33 (without institutions) to 0.69 in Table 1, column (4), does not remove the statistical significance of GDP per capita. Controlling for institutional quality, although it is highly significant, does not solve the Lucas puzzle of 'uphill' capital flows. Importantly, this model has much improved diagnostics compared to the linear-log or linear-linear model. Plotting the residuals from the IHS-log model against its fitted values (Figure 3b) shows no obvious heteroskedastic pattern, whereas in AKV's linear-log model the residuals are much more widely spread at higher fitted values (Figure 3a). AKV report heteroskedasticity-robust standard errors; this is a response to the symptoms of heteroskedasticity but does not solve the underlying problem if this is due to model misspecification (Zietz 2001). Moreover, we find there is a larger difference between robust and conventional standard errors if we use the linear-log model, which is symptomatic of misspecification (Hendry and Nielsen 2007, pp.133-134; King and Roberts 2015); in contrast, the two types of standard errors are almost the same in the IHS-log model.[4]

However, normality of the errors is still convincingly rejected in the IHS-log model in column (4), which may be due to the existence of outliers. To examine the effect of outliers

[4] In particular, for the coefficient of the log of GDP per capita, the conventional standard error (.20) is more than 50% larger than the robust standard error (.13) in the linear-log model (Table 1, column (2)), compared to 0.25 and 0.28, respectively, in the IHS-log model (Table 1, column (4)). Differences between conventional and robust standard errors are also suggestive of model misspecification in the linear-linear model.

on residual normality, we first informally identify outliers by examining plots of leverage against squared residuals, and residuals against fitted values. In AKV's linear-log model (Table 1, column (2)), six observations from their 98-country whole world sample are identified as outliers (Great Britain, Netherlands, Denmark, Sweden, Finland and Singapore). If these observations are excluded, the coefficient on the log of GDP per capita retains statistical significance at the 10% level even when controlling for institutional quality (Table 1, column (5)), suggesting that AKV's resolution of the Lucas Paradox may be sensitive to the inclusion of outliers. However, more importantly, removal of these outliers does not solve the problem of non-normal residuals and the other diagnostics suggest misspecification, so inference based on this functional form is still unreliable.[5]

Undertaking a similar exercise for the IHS-log model leads to eight observations being identified as outliers (Singapore, South Africa, Trinidad and Tobago, Sweden, Ukraine, Senegal, Iran, and Zimbabwe). If these are removed from the sample, there is a marked improvement in the diagnostics, with no evidence of residual non-normality, heteroskedasticity or functional form misspecification (Table 1, column (6)). For this sample, the evidence for the Lucas Paradox remains, despite the inclusion of institutional quality in the model, with the coefficient on the log of GDP per capita now larger and significant at the 1% level.

We reach a similar conclusion for AKV's Base Sample (Columns (7) to (14)), i.e. inclusion of the index of institutions appears to render the coefficient on the log of GDP per capita statistically insignificant in AKV's linear-log model (cf. columns (7) and (8) for the PWT measure of GDP per capita, or (11) and (12) for the WDI measure).[6] However,

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[5] A similar problem arises with the linear-linear model in Table 1, column (3). Omitting outliers (Great Britain, Netherlands, Denmark, Sweden and Finland), the log of GDP per capita remains statistically significant at the 1% level, but the diagnostic test results imply that inference based on this model remains unreliable.

[6] AKV also report results with the PWT measure of GDP per capita averaged over the period 1970-2000 (their Table 3, columns (6) and (7)). However, the results in their column (6) appear to report the coefficient estimate

essentially zero *p*-values for all the diagnostic tests for all these models provide strong evidence of misspecification of the linear-log model. For the IHS-log model, the PWT measure of GDP per capita loses statistical significance when the index of institutional quality is added (column (9)); in contrast, the WDI measure retains its statistical significance when institutional quality is added (column (13)). The IHS-log model (for both measures of GDP per capita) again has much improved diagnostics compared to the linear-log model but normality of the errors is still convincingly rejected. If we delete observations identified as outliers, there is no evidence of residual non-normality, heteroskedasticity or functional form misspecification (Table 1, column (10)).[7] For this model, the coefficient on the log of GDP per capita is quantitatively and statistically significant (at the 1% level) despite the inclusion of institutional quality as a regressor. A similar result is obtained if (the same) outliers are deleted from the model using the WDI definition of GDP per capita (Table 1, column (14)).

To complement the graphical approach, we also apply impulse-indicator saturation (IIS) to detect and remove outliers (Hendry, Johansen, and Santos 2008; Johansen and Nielsen 2009; Hendry and Doornik 2014), as implemented in *Autometrics* in OxMetrics, version 7 (Doornik and Hendry 2013). This approach creates a set of mutually orthogonal dummy variables (impulse indicators), one for each observation. Hendry, Johansen, and Santos (2008) and Johansen and Nielsen (2009) consider the distributional properties of the IIS estimator in its simplest form where half of the indicators are initially included in the model, along with the set of conventional candidate regressors, and the significant impulse indicators noted. All first-half indicators are then dropped; the process is repeated with the remaining half of the indicators entered, and the significant second-half indicators noted. The significant indicators from both stages are then combined in a model including the candidate regressors to select

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and standard error for the 1970 PWT values of GDP per capita. We were unable to reproduce the results in their column (7) from their data.

[7] The outliers identified are the same as the eight countries for the Whole World sample (Singapore, South Africa, Trinidad and Tobago, Sweden, Ukraine, Senegal, Iran, and Zimbabwe) plus Israel. Similar qualitative results are obtained if just the original eight observations are omitted.

the final set of significant variables and indicators (Hendry and Doornik 2014, Ch. 15). Analytical derivation of the asymptotic sampling distribution of the IIS estimator (Hendry, Johansen, and Santos 2008; Johansen and Nielsen 2009) and Monte Carlo evidence (Hendry and Doornik 2014) imply that including an impulse indicator for every observation need not lead to any significant loss in efficiency if they are all irrelevant, but performs well in detecting outliers when they are present. When applied to models with fat-tailed error distributions, much of the non-normality can be picked up by the impulse indicators, so that using critical values based on normality for inference is reasonable (Castle, Doornik, and Hendry 2012; Doornik and Hendry 2014, Ch. 15.6).

The variant of IIS implemented in *Autometrics*' multi-path search algorithm uses several block divisions corresponding to different-sized sample splits (e.g. *N*/3, *N*/4, *N*/5) rather than the simple 'split-half' version. A tight significance level is used (0.01), giving one chance in 100 of retaining an impulse indicator if there are no outliers. For the IHS-log functional form and the whole world sample, with the significance level set at 0.01, *Autometrics* selects impulse indicators for the same eight observations detected as outliers using the graphical methods outlined above (Singapore, South Africa, Trinidad and Tobago, Sweden, Ukraine, Senegal, Iran, and Zimbabwe) as well as the log of GDP per capita and institutional quality. Including the impulse indicators in the final model is equivalent to omitting the effect of these observations on other parameter estimates in the model, so the coefficient estimates and standard errors for our variables of interest are the same as in Table 1, column (6).[8] As already noted, this model passes the diagnostic tests and reveals GDP per capita to be statistically significant at the 1% level, despite including institutional quality as a highly significant regressor.[9]

[8] Deleting outliers identified graphically is reflected in Tables 1 and 2 by a reduction in the number of observations (*N*); retaining impulse indicators (as in some models in Tables 2, 3 and 4) leaves *N* unaffected.

[9] Applying IIS to the linear-log and linear-linear functional forms retains GDP per capita as a significant explanatory variable in the selected linear-linear model but not the log of GDP per capita in the linear-log

As well as institutional quality, AKV examine other proposed explanations of the Lucas Paradox, such as years of schooling, distantness, and capital controls. They conclude that these factors are far less important than institutional quality in explaining cross-country differences in capital flows. We reproduce (in Appendix Table A1) the results in their Table 4, but find that *all* the models they report clearly fail the diagnostic tests (with p = 0.00 for all four misspecification tests for each of the models).[10] The results from fitting the equivalent of these models using the IHS-log functional form for the partial relationship between capital flows and GDP per capita are reported in Table 2. The log of GDP per capita retains statistical significance if these other variables are added individually (columns (1) to (6)); however, if all variables are included, as in columns (7) and (9), institutional quality is statistically significant (although only at the 10% level in column (9)) but the coefficient on the log of GDP per capita is no longer significant. This appears to support AKV's contention; however, although heteroskedasticity and RESET tests no longer reject their respective null hypotheses for any of the models in Table 2, columns (1) to (7) and (9), normality of the errors is still decisively rejected in all these models.

Based on examination of plots of leverage against squared residuals, and residuals against fitted values, the same eight observations identified previously appear as outliers in the extended models in Table 2, columns (7) and (9). If we delete these observations (as in columns (8) and (10)), normality of the errors is no longer rejected, although heteroskedasticity reappears in the model including the PWT measure of GDP per capita in column (8). For the sample without the eight outliers, institutional quality, log of GDP per

model. However, for both these functional forms, the final selected model includes large numbers of impulse indicators (24 for linear-log and 41 for the linear-linear model) and fails the diagnostic tests. These results provide further support for the IHS-log model as the most reliable basis for inference of the three models considered.

[10] The Barro and Lee (2001) data set provides schooling data for 82 countries out of AKV's 98 country sample, although AKV report that N=92 in column (1) of their Table 4. AKV's own data set also contains schooling data for only 82 countries.

capita and log of years of schooling are statistically significant for both measures of GDP; so, again, the Lucas Paradox does not disappear.

We also apply the *Autometrics* model selection algorithm, with IIS, to the models in Table 2, columns (7) and (9). For the WDI measure of GDP per capita, impulse indicators for Bangladesh and Belarus are selected as well as the eight previously identified outliers; however, the distantness and capital restrictions variables are removed by the algorithm. The estimates for the parameters of interest and diagnostics, reported in column (11), imply institutional quality, log of GDP per capita and log of years of schooling are all statistically significant at the 1% level.

For the PWT measure of GDP the results are less conclusive. *Autometrics* arrives at a final general unrestricted model (GUM) and four different terminal models with between 11 and 13 impulse indicators. All the models include institutional quality and years of schooling; the final GUM and two of the terminal models include log of GDP per capita, but the other two models exclude it. Representative results are presented in Table 2, columns (12) and (13). Column (12) reports one of the terminal models in which the PWT definition of log GDP per capita is not selected; compared to the model in column (13), in which the log of GDP per capita is included, the coefficients on institutional quality and log average schooling in column (12) are notably larger in magnitude. In contrast, in column (13), the log of GDP per capita has a statistically significant coefficient at the 1% level using conventional standard errors (and the 5% significance level using robust standard errors), and its approximate elasticity is quantitatively significant. The statistical significance of the PWT measure of log GDP per capita in this case is therefore sensitive to the choice of observations dummied out by the selected impulse indicators.[11]

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[11] The model that excludes the log of GDP per capita in column (12) includes 13 country dummies (for Bangladesh, Belarus, Bulgaria, Iran, Israel, Kenya, Senegal, Singapore, South Africa, Sweden, Trinidad and Tobago, Ukraine and Zimbabwe), whereas the model that includes the highly significant GDP per capita variable in column (13) includes 11 country dummies (omitting Bulgaria and Israel from the earlier list). The

To sum up, the main message of this replication exercise is that, in appropriately specified models (i.e. for which there is no evidence of obvious misspecification), institutional quality, although a highly significant determinant of capital flows, cannot fully resolve the Lucas Paradox.[12] Our results suggest that the lack of statistical significance of GDP per capita in AKV's results is due to model misspecification and/or is dependent on outliers.

Our conclusions are in agreement with and complement those of Azémar and Desbordes (2013) who argue that AKV's result is not robust to the removal of outliers and, on the basis of goodness of fit, prefer a log-log model; their results also suggest that institutional quality contributes significantly to explaining variation in capital inflows, but does not resolve the Lucas Paradox. It is worth emphasizing that, although we reach similar conclusions, our analysis differs from that of Azémar and Desbordes in several ways. AKV use the IMF's IFS capital flows data for their main analysis and use capital stock data, including LM's (2007, updated 2012) data, for robustness checking. We use AKV's original data set for IFS capital flows for the replication results in this section. Azémar and Desbordes's analysis is based solely on the LM data, and it is not clear from their analysis whether differenced capital stock data behave in the same way as capital flows in respecified models. Methodologically, the most important difference is that Azémar and Desbordes's choice of preferred models is based purely on goodness-of-fit; in contrast, our selection of model specification is based on diagnostic testing of the underlying statistical assumptions that underpin inference (normality, homoskedasticity, and correct functional form).[13] This is particularly critical

models are very similar in terms of goodness-of-fit and both pass all diagnostic tests, although more marginally for homoskedasticity for the model in column (12). *Autometrics* selects the model in column (12) as its (marginally) preferred model on the basis of its 'tie-breaker', the Schwarz Criterion (SC = 2.43 in (12) compared to 2.44 in (13)).

[12] In addition to GDP per capita and institutional quality, years of schooling (i.e. human capital) has a statistically significant positive effect on capital inflows in the IHS-log model, while restrictions to the capital account, significant in AKV's linear-log model (their Table 4), is no longer statistically significant.

[13] In addition, Azémar and Desbordes use a robust estimation method to identify outliers, whereas we use IIS and leverage and residual plots.

given that, in AKV's approach, the statistical significance of the coefficient on GDP per capita is the acid test for the existence of the Lucas Paradox.

IV. Cross-section analysis using an extended dataset, 1984-2011

We also examine the determinants of real capital inflows using a dataset covering the extended period 1984 to 2011 with country coverage matching AKV's Whole World Sample.[14] The dependent variable is the sum of direct (i.e. FDI) and portfolio equity inflows. In line with most of the literature on the Lucas Paradox, these inflows are gross inflows net of disinvestment and profit repatriation (not net inflows, i.e. inflows minus outflows). The models estimated in this section include the explanatory variables considered by AKV as well as additional controls. The data are taken from two different sources: annual inflows data of direct and portfolio equity are taken from the IMF's IFS and, as an alternative, we also use differenced capital stock data from LM's (2007, updated 2012) direct and portfolio equity stock data set. We fit linear-log and log-log models, using data averaged over the full time period (1984-2011) and compare the results with those obtained using AKV's data in section II.[15]

For institutional quality we use two alternative measures: the Political Risk Services (PRS) Group's ICRG 'political risk' rating (the sum of the annual rating of 12 components) and the World Bank's Worldwide Governance Indicators (WGI) (comprising six governance dimensions) (Kaufmann et al. 2010).[16] We use real GDP per capita (PPP) in the base year period (1984), from the Penn World Table (PWT 7.1) (Heston, Summers, and Aten 2012), as a measure of economic development. Human capital, a fundamental determinant of capital

[14] We retain AKV's (2008) sample of countries to maximize comparability with AKV's results.

[15] Because the data are temporally averaged over the full period, average per capita capital inflows are positive for all countries, except for Gabon. Using a conventional log transformation of the dependent variable therefore involves losing only one observation.

[16] The political risk indicator used by AKV is an average of 11 subcomponents; the institutional quality variable in our extended data set is a more recent version of the PRS Group's index that aggregates 12 subcomponents, including 'Socioeconomic Conditions'.

inflows, is proxied by (the logarithm of) average years of schooling, from Barro and Lee (2013). To control for capital market imperfections/frictions, we use the *de jure* measure of capital account openness constructed by Chinn and Ito (2008). Additional controls include: distantness (measured by distance from the capital city of a country to capital cities of other countries) as a proxy for remoteness (Mayer and Zignago 2011), trade openness (measured by the sum of export and imports as a proportion of GDP) (World Bank 2013), financial market development (measured by credit to the private sector as a proportion of GDP) (Beck, Demirgüç-Kunt, and Levine 2000, 2010), and average inflation (as a proxy for macroeconomic stability) (World Bank 2013).

Table 3 reports cross-sectional estimates using the extended dataset. The results are consistent with our findings using AKV's dataset. Initial inspection suggests that institutional quality (using the ICRG measure) resolves the Lucas Paradox if the dependent variable enters linearly (comparing columns (1) and (2)), but not if it is log-transformed (column (3)). Using the WGI's aggregated Governance Index to measure institutional quality, the results suggest institutional quality cannot solve the Lucas Paradox, even when the dependent variable is entered linearly (columns (4) and (5)). The model in column (6) adds a version of each of the additional control variables (distantness, capital controls, and years of schooling) proposed by AKV to the log-log model and finds the Paradox is still not resolved. If we include proxies for additional standard determinants of capital inflows (trade openness, financial development, and macroeconomic stability) (in columns (7) and (8)), the Lucas Paradox still persists.[17] However, the diagnostics decisively reject the hypothesis of normality of the errors in all of these models, potentially undermining the validity of inference.

Visual inspection of plots of residuals against fitted values reveals the presence of outliers. Applying IIS and *Autometrics*' selection algorithm to the models in columns (3), (7)

[17] Schooling data are available for fewer countries than the other variables, so we present results including and excluding schooling, as the latter gives a larger sample coverage.

and (8), we obtain the models reported in columns (9), (10) and (11). These models contain a limited number of country dummies (reported in the notes to Table 3) but, unlike the other models reported in the table, they pass all the diagnostic tests, including tests for normality. They, therefore, provide a more reliable basis for testing the significance of the estimated coefficients. As for the AKV data, models satisfying the assumptions required for valid inference continue to show the coefficient on the log of GDP per capita to be quantitatively and statistically significant.[18]

The results in Table 4 are based on an alternative source of capital inflows: the LM data obtained by first differencing the stock data of direct and portfolio equity. The IMF's IFS capital flow data do not incorporate potentially large valuation effects. Capital stock data measure the long-run asset holding positions of a country and LM's estimates adjust for valuation effects. Examination of the LM data allows us to verify the robustness of our estimates to alternative measure of the dependent variable and to provide a direct comparison with Azémar and Desbordes's (2013) results.

Columns (1) and (2) report estimates for the linear-log model. The results are similar to those obtained using the IFS capital flow data: the coefficient on the log of GDP per capita loses statistical significance when an index of institutional quality is included. However, the log of GDP per capita retains its statistical significance in the log-log model for both institutional quality proxies considered (columns (3) and (4)).[19] Adding variables representing other possible explanations of the Lucas Paradox (column (5)) does not change this result. The models in columns (4) and (6) are similar to the models in Azémar and Desbordes's (2013) Table 4, columns [5′] and [6′], respectively, and, as for their results,

[18] In contrast, applying IIS to the linear-log model in column (2), for example, adds multiple (34) country dummies to the selected model and the 'best' model selected still fails diagnostic tests for normality, heteroskedasticity and functional form. Similar problems occur when applying IIS to the linear-log equivalents of the more general models in Table 3. Using IIS with IHS equivalents of these models leads to selected models that fail RESET tests, so the log-log specification is preferred for our extended dataset.

[19] For the LM data, all values of the differenced stocks are positive, so we use a conventional log transformation for the dependent variable. Very similar results are obtained if we use the IHS transformation.

display a statistically and quantitatively significant coefficient on the log of initial GDP per capita. Again, a pervasive problem with these models is rejection of normality of the errors due to outliers. Applying IIS and model selection to the models in columns (3), (5) and (6), we obtain the results in columns (7), (8) and (9) (with country dummies included to deal with outliers reported in the notes to Table 4); these fitted models pass all the diagnostic tests and the log of initial GDP per capita remains quantitatively and statistically significant.

V. Instrumental variables estimation results

Although most of AKV's analysis is based on OLS regressions, they also consider the possibility that institutional quality may be endogenous, primarily because of reverse causality, e.g. due to increased capital inflows creating incentives to reform institutional structures. Following Acemoglu, Johnson, and Robinson (2001), they use the log of the European settler mortality rate as an instrument for institutional quality, which reduces their sample size from 98 countries (81 in the base sample) to 45 countries. Their two-stage least squares (2SLS) results using IFS data (their Table 11, column (2)) are reproduced in Table 5, column (1). We also include details of first-stage regressions/reduced forms for endogenous explanatory variables and the reduced form for capital flows, i.e. the dependent variable.[20] Taken at face value, the 2SLS results for AKV's linear-log functional form in column (1) imply institutional quality has a statistically significant effect on per capita capital inflows but the log of GDP per capita is not statistically significant, consistent with their OLS results. However, although there is no obvious sign of misspecification of the first-stage regression for institutional quality (in column (2)), the reduced form for the dependent variable, capital flows per capita entered linearly (column (1)), shows evidence of non-normality of the errors, heteroskedasticity and functional form misspecification, similar to the OLS results in Table 1.

[20] Spanos (2007) emphasizes that statistical adequacy (the validity of the underlying statistical assumptions) of the full set of reduced forms, which provides an embedding framework for the structural equation of interest, underpins the validity of inference.

Even if we dismiss these features of the reduced form for capital flows, a weak identification test, *CD-F*, implies weak instrumentation, which can badly bias estimates and distort the size of tests and coverage of confidence intervals.[21]

Applying 2SLS to the model with IHS-transformed capital inflows per capita as the dependent variable (Table 5, column (3)), neither institutional quality nor the log of GDP per capita is statistically significant. In the reduced form for the IHS-transformed dependent variable, there is evidence of non-normality of the errors but the rest of the diagnostics are not problematical.[22]

Regardless of functional form assumptions, another important concern is that, although institutional quality is treated as potentially endogenous, AKV assume the log of GDP per capita is exogenous; it therefore enters the instrument set and, as can be seen in columns (1) to (3), dominates the explanatory power of the first-stage regression for institutional quality and the reduced form for per capita capital flows. However, capital inflows plausibly have a positive effect on GDP per capita. Moreover, the deep determinants literature (e.g. Acemoglu, Johnson, and Robinson 2001) emphasizes that institutional quality (which AKV assume to be potentially endogenous) is a fundamental cause of long-run differences in levels of GDP per capita, which implies that if institutions are considered potentially endogenous then GDP per capita is also likely to be endogenous. AKV's model includes GDP per capita in the base-year (1970), which arguably would reduce the endogeneity problem. However, in a pure cross-section analysis, the variation being exploited is across countries rather than across time, so that use of lagged variables may not remove endogeneity.[23]

[21] *CD-F* is the Wald *F*-statistic form of Cragg and Donald's (1993) test for the null of weak instruments and is compared to critical values based on test size distortion; non-rejection implies instruments are weak. Based on Stock and Yogo's (2005) critical values, a *CD-F* value as small as 2.99 is not statistically significant at even a 25% maximal size.

[22] Similar results are obtained if a conventional log transformation is used for the dependent variable (based on a sample with $N = 44$).

[23] The correlation between the averaged ICRG institutional quality measure and GDP per capita in 1970 (in PPP terms,1996 prices) is 0.85 in AKV's base sample of 81 countries, compared to a correlation of 0.37 between institutional quality and GDP per capita (in PPP terms,1996 prices) averaged over 1970-2000.

Columns (4) to (7) explore the implications of treating the log of GDP per capita as potentially endogenous. This requires at least one additional instrument, so we include the instruments used by AKV in their Table 12: a dummy variable for British legal origin and the fraction of the population speaking English as their first language, as well as the log of European settler mortality. With capital flows per capita entered linearly, institutional quality has a significant effect but log of GDP per capita is not significant. For the IHS-transformed dependent variable, the opposite result is obtained: the log of GDP per capita is significant but not institutional quality. The reduced form for capital flows per capita entered linearly (column (4)) again shows evidence of non-normality of the errors, heteroskedasticity and functional form misspecification; there is also some evidence of heteroskedasticity and functional form misspecification in the reduced form for the IHS-transformed capital flows dependent variable. The very small *CD-F* value again implies weak instruments, which applies to both models as they share common explanatory variables and a common instrument set. Taken at face value, the Sargan (1958) test implies rejection of the overidentifying restrictions.[24] Overall, the ability of institutions to resolve the Lucas Paradox again appears to be sensitive to choice of functional form and is subject to concerns over the weakness of the instruments in AKV's instrumentation strategy.

Results from fitting similar models using the extended data set are reported in Table 6. Again, choice of functional form makes a dramatic difference. For the linear-log model with the log of GDP per capita treated as exogenous (columns (1) and (2)), institutional quality is statistically significant, but not log of GDP per capita; for the log-log model (columns (2) and (3)), the reverse is the case. A similar set of contrasting results is obtained when the models are compared but the log of GDP per capita is treated as endogenous and instrumented using the same set of instruments as in Table 4. In this comparison, the reduced form for the linear

[24] Testing the overidentifying restrictions using Hansen's (1982) *J* statistic, which is consistent in the presence of heteroskedasticity, gives qualitatively similar results.

form of capital flows per capita appears to have more far-reaching misspecification problems than the log form, casting further doubt on the hypothesis that institutional quality resolves the Lucas Paradox.

VI. Conclusion

The Lucas Paradox, the tendency for capital to flow predominantly to relatively rich countries in contradiction to the neoclassical prediction that it should flow from low-return, capital-abundant to high-return, capital-scarce economies, has proved to be resistant to empirical attempts to find a compelling resolution. However, AKV's (2008, p.354) argue that "institutional quality is the variable that explains the Lucas Paradox": when institutional quality is included in regression models explaining international capital inflows, they contend that a country's level of economic development, as measured by its log of GDP per capita, is no longer statistically significant.

We replicate AKV's results, using their cross-sectional IFS data. Motivated by the importance of conducting inference in statistically adequate models, we focus on misspecification testing of alternative functional forms of their empirical model of capital flows. We show that AKV's resolution of the Paradox finding relies on inference in a misspecified model and/or is dependent on outlier observations. If a more appropriately specified model is employed, institutional quality, although a statistically and quantitatively significant determinant of capital inflows, does not fully account for the Lucas paradox: a country's level of economic development remains a significant determinant of capital inflows even if controlling for a country's institutional quality. Our estimates from appropriately specified models, judged on the basis of a battery of misspecification tests, complement the findings of Azémar and Desbordes (2013). We show that our results are robust using both

AKV's IFS capital flow data and more recent capital flow, first-differenced capital stock and institutions data with additional controls.

In models that do not fail basic misspecification tests, a country's level of economic development is a significant predictor of capital inflows. As well as institutional quality, there is evidence that other factors such as human capital and trade openness are statistically significant determinants of capital inflows. However, none of these determinants fully accounts for why capital tends to flow predominantly to relatively rich countries. Rather, the Lucas paradox stands, as yet, unresolved.

Table 1. Replication and extension of OLS regression results in AKV's Table 3

	Whole World Linear (1)	Whole World Linear (2)	Whole World Linear (3)	Whole World IHS (4)	Whole World Linear (5)	Whole World IHS (6)	Base Sample Linear (7)	Base Sample Linear (8)	Base Sample IHS (9)	Base Sample IHS (10)	Base Sample Linear (11)	Base Sample Linear (12)	Base Sample IHS (13)	Base Sample IHS (14)
Log GDP per capita (PPP), 1970	1.05***	0.20		0.69**	0.20*	0.98***	1.18***	0.14	0.42	0.72***				
	(0.17)	(0.13)		(0.28)	(0.11)	(0.18)	(0.19	(0.20)	(0.39)	(0.21)				
Log GDP per capita, ($1996) 1970											0.84***	0.20	0.49**	0.58***
											(0.14)	(0.13)	(0.23)	(0.14)
GDP per capita, (PPP), 1970			0.01***											
			(0.004)											
Average institutional quality, 1984-2000		0.68***	47.58***	0.51***	0.54***	0.47***		0.75***	0.63**	0.59***		0.67***	0.47**	0.51***
		(0.14)	(12.14)	(0.19)	(0.10)	(0.10)		(0.17)	(0.25)	(0.12)		(0.15)	(0.23)	(0.12)
R^2	0.37	0.52	0.56	0.47	0.58	0.79	0.39	0.52	0.44	0.82	0.44	0.53	0.46	0.83
Observations	98	98	98	98	92	90	81	81	81	72	81	81	81	72
Norm-p	0.00	0.00	0.00	0.00	0.01	0.58	0.00	0.00	0.00	0.35	0.00	0.00	0.00	0.42
Hetero-p	0.00	0.00	0.00	0.81	0.00	0.13	0.00	0.00	0.74	0.25	0.00	0.00	0.68	0.51
HeteroX-p	0.00	0.00	0.00	0.75	0.00	0.17	0.00	0.00	0.54	0.36	0.00	0.00	0.79	0.65
RESET-p	0.00	0.00	0.00	0.42	0.00	0.21	0.00	0.00	0.62	0.31	0.00	0.00	0.74	0.07
RMSE	1.26	1.11	106.31	1.40	0.74	0.79	1.33	1.19	1.46	0.72	1.29	1.19	1.44	0.70

Notes: IHS denotes inverse hyperbolic sine transformation of the dependent variable (capital inflows per capita); Linear denotes the dependent variable enters linearly. All models include an intercept term. Models in columns (5), (6), (10) and (14) exclude outliers. Diagnostic tests: *p*-values are reported. Robust standard errors are in parentheses; ***, ** and * denote statistical significance at the 1%, 5% and 10% levels, respectively. As with AKV, the 98-country whole world sample includes all countries with data available for per capita inflows, GDP per capita, and the index of institutions and excludes countries with population less than a million. The base sample includes the 81 countries for which all the other main explanatory variables (used in Table 2) are available.

Table 2. OLS regression results for the IHS-log functional form equivalent of models in AKV's Table 4

	Whole World IHS (1)	Whole World IHS (2)	Whole World IHS (3)	Base Sample IHS (4)	Base Sample IHS (5)	Base Sample HIS (6)	Base Sample IHS (7)	Base Sample IHS (8)	Base Sample IHS (9)	Base Sample IHS (10)	Base Sample IHS (11)#	Base Sample IHS (12)#	Base Sample IHS (13)#
Log GDP per capita (PPP) 1970	0.86*** (0.24)	1.30*** (0.16)	1.12*** (0.19)	0.88*** (0.24)	1.27*** (0.19)	1.06*** (0.21)	0.07 (0.40)	0.56** (0.23)					0.50*** (0.19)
Log GDP per capita ($1996) 1970									0.30 (0.26)	0.47*** (0.16)	0.43** (0.13)		
Average institutional quality, 1984-2000							0.51** (0.23)	0.48*** (0.12)	0.39* (0.22)	0.43*** (0.12)	0.42*** (0.10)	0.69*** (0.07)	0.47*** (0.09)
Log average schooling 1970-2000	0.71** (0.28)			0.67** (0.28)			0.53** (0.24)	0.47*** (0.16)	0.35 (0.29)	0.40** (0.17)	0.50*** (0.18)	0.72*** (0.14)	0.56*** (0.17)
Log average distantness		–0.32 (0.66)			–0.31 (0.72)		–0.15 (0.70)	0.51* (0.30)	–0.11 (0.70)	0.48 (0.30)			
Average restrictions to capital mobility			–1.41* (0.76)			–1.72* (0.87)	–1.20 (0.75)	–0.62 (0.41)	–1.11 (0.73)	–0.60 (0.38)			
R^2	0.39	0.42	0.44	0.39	0.37	0.41	0.48	0.84	0.48	0.85	0.91	0.92	0.92
Observations	82	97	97	81	81	81	81	73	81	73	81	81	81
Norm-p	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.57	0.00	0.24	0.13	0.31	0.22
Hetero-p	0.48	0.38	0.58	0.46	0.18	0.60	0.63	0.02	0.62	0.20	0.48	0.09	0.24
HeteroX-p	0.60	0.52	0.49	0.59	0.27	0.52	0.46	0.02	0.71	0.13	0.31	0.09	0.31
RESET-p	0.43	0.27	0.57	0.46	0.34	0.62	0.72	0.24	0.76	0.123	0.78	0.97	0.73
RMSE	1.53	1.47	1.44	1.53	1.56	1.50	1.45	0.69	1.44	0.68	0.63	0.59	0.62

Notes: IHS denotes inverse hyperbolic sine transformation of the dependent variable, capital flows per capita. All models include an intercept term. Models in columns (8) and (10) exclude outliers identified by graphical methods. Models in columns (11) to (13) include selected impulse indicators applying IIS. Diagnostic tests: *p*-values are reported. Robust standard errors are in parentheses, except for columns marked #, which report conventional standard errors; ***, ** and * denote statistical significance at the 1%, 5% and 10% levels, respectively.

Table 3. **OLS regression results for the extended data set, 1984-2011**

	Linear (1)	Linear (2)	Log (3)	Linear (4)	Log (5)	Log (6)	Log (7)	Log (8)	Log (9)#	Log (10)#	Log (11)#
Log GDP per capita (PPP),	2.55***	0.39	0.89***	0.41**	0.89***	0.64*	0.49*	0.65***	0.92***	0.68***	0.86***
1984	(0.44)	(0.27)	(0.24)	(0.19)	(0.20)	(0.36)	(0.28)	(0.24)	(0.11)	(0.12)	(0.09)
Average institutional quality,		0.19***	0.05***			0.05***	0.05***	0.05***	0.04***	0.04***	0.04***
ICRG, 1984-2011		(0.04)	(0.02)			(0.02)	(0.02)	(0.01)	(0.01)	(0.01)	(0.01)
Average governance index,				0.62***	0.16***						
WGI, 1996-2011				(0.12)	(0.05)						
Average capital account openness,						0.17	0.13	0.13			
1984-2011						(0.11)	(0.10)	(0.10)			
Log average schooling,						0.11	0.08			0.24	
1985-2010						(0.32)	(0.22)			(0.17)	
Log average distantness						0.25	0.33	0.32			
						(0.32)	(0.30)	(0.29)			
Log average trade							0.69	0.81***		0.51***	0.67***
							(0.18)	(0.18)		(0.12)	(0.12)
Log average financial development							0.18	0.18			
							(0.15)	(0.14)			
Log average inflation							0.11	0.13			0.10**
							(0.07)	(0.06)			(0.04)
R^2	0.33	0.45	0.76	0.50	0.78	0.77	0.81	0.82	0.90	0.92	0.93
Observations	98	98	97	98	97	88	86	93	97	87	93
Norm-p	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.89	0.79	0.19
Hetero-p	0.12	0.46	0.42	0.29	0.09	0.46	0.87	0.79	0.13	0.35	0.10
HeteroX-p	0.12	0.55	0.12	0.43	0.01	0.22	0.91	0.85	0.17	0.14	0.15
RESET-p	0.00	0.00	0.29	0.00	0.03	0.04	0.56	0.74	0.15	0.79	0.61
RMSE	4.32	3.94	0.99	3.76	0.95	0.97	0.85	0.87	0.67	0.55	0.54

Notes: Linear denotes the dependent variable enters linearly; Log denotes conventional logarithmic transformation of the dependent variable. All models include an intercept term. Diagnostic tests: *p*-values are reported. Robust standard errors are in parentheses, except for columns marked #, which report conventional standard errors; ***, ** and * denote statistical significance at the 1%, 5% and 10% levels, respectively. Models in columns (9), (10) and (11) include selected impulse indicators: (9) for Iran, Madagascar and Zimbabwe; (10): Iran, Kenya; (11): Chile, Iran, Kenya, Madagascar.

Table 4. OLS regression results using LM flow data, 1984-2011

	Linear	Linear	Log	Log	Log	Log	Log	Log	Log
VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	(7)#	(8)#	(9)#
Log GDP per capita (PPP),1984	3.32***	0.51	0.79***	0.88***	0.72***	0.65***	0.78***	0.54***	0.70***
	(0.66)	(0.32)	(0.12)	(0.11)	(0.18)	(0.16)	(0.09)	(0.13)	(0.04)
Average institutional quality		0.25***	0.05***		0.05***		0.05***	0.05***	
ICRG, 1984-2011		(0.05)	(0.01)		(0.01)		(0.01)	(0.01)	
Average governance index				0.14***		0.15***			0.13***
WGI, 1996-2011				(0.02)		(0.03)			(0.01)
Average capital account openness					0.09	0.03			
					(0.08)	(0.08)			
Log average distantness					–0.0002	–0.20			
					(0.27)	(0.25)			
Log average trade					0.76***			0.60***	
					(0.18)			(0.14)	
Log average financial development					0.14				
					(0.17)				
Log average inflation					0.14*				
					(0.08)				
Log average schooling, 1985-2010					–0.04	0.42**		0.35*	0.45***
					(0.28)	(0.21)		(0.19)	(0.16)
R^2	0.28	0.38	0.83	0.83	0.87	0.84	0.89	0.90	nc
Observations	98	98	98	98	87	89	98	88	89
Norm-p	0.00	0.00	0.00	0.00	0.01	0.00	0.59	0.96	0.35
Hetero-p	0.18	0.54	0.29	0.18	0.26	0.17	0.66	0.09	0.33
HeteroX-p	0.18	0.63	0.38	0.28	0.49	0.56	0.62	0.10	0.60
RESET-p	0.00	0.00	0.19	0.23	0.78	0.10	0.16	0.41	0.10
RMSE	6.38	5.97	0.76	0.75	0.70	0.76	0.62	0.61	0.57

Notes: Linear denotes the dependent variable enters linearly; Log denotes conventional logarithmic transformation of the dependent variable. All models include an intercept term, except (nc) for column (9). Diagnostic tests: *p*-values are reported. Robust standard errors are in parentheses, except for columns marked #, which report conventional standard errors; ***, ** and * denote statistical significance at the 1%, 5% and 10% levels, respectively. Models in columns (7), (8) and (9) include selected impulse indicators: (7) and (9) for Bangladesh, Congo, Iran and Singapore; (8): Bangladesh and Kenya.

Table 5. Replication and extension of 2SLS results in AKV's Table 11

	Linear (1)	(2)	IHS (3)	Linear (4)	(5)	(6)	IHS (7)
Log GDP per capita	−1.18		0.79	−0.31			3.93*
(PPP), 1970	(1.09)		(1.52)	(0.84)			(2.37)
Average institutional	1.76**		0.39	1.17**			−1.72
quality, 1984-2000	(0.85)		(1.25)	(.58)			(1.72)
RMSE	1.078		1.328	0.82			2.24
CD-F		2.99			1.28		
Sargan-p		na		1.00			0.94
Reduced forms		*Inst*			*Inst*	*lnGDPpc*	
Log settler mortality	−0.47**	−0.27*	−0.10	−0.60***	−0.63***	−0.44***	−0.69*
	(0.18)	(.15)	(0.37)	(0.20)	(0.13)	(0.09)	(0.38)
Log GDP per capita	0.65***	1.04***	1.19***				
	(0.16)	(0.17)	(0.34)				
British legal origin				−0.22	−0.34	−0.58***	−1.69***
				(0.23)	(0.33)	(0.21)	(0.61)
English language				1.58**	1.68***	1.30***	2.13**
				(0.77)	(0.57)	(0.32)	(0.92)
R^2	0.56	0.68	0.35	0.56	0.53	0.61	0.36
Norm-p	0.06	0.39	0.00	0.04	0.52	0.84	0.12
Hetero-p	0.00	0.95	0.71	0.00	0.07	0.30	0.22
HeteroX-p	0.00	0.98	0.82	0.00	0.04	0.29	0.02
RESET-p	0.00	0.09	0.53	0.00	0.42	0.06	0.03

Notes: IHS denotes inverse hyperbolic sine transformation of the dependent variable (capital inflows per capita); Linear denotes the dependent variable enters linearly. *Inst* and *lnGDPpc* denote the endogenous explanatory variables institutional quality and log of GDP per capita, respectively. All models include an intercept term. Diagnostic tests: *p*-values are reported. Robust standard errors are in parentheses; ***, ** and * denote statistical significance at the 1%, 5% and 10% levels, respectively. N = 45 for all regressions. The reduced forms in columns (1) and (2) [(2) and (3)] correspond to the 2SLS estimates in column (1) [(3)]; similarly, the reduced forms in columns (4), (5) and (6) [(5), (6) and (7)] correspond to the 2SLS estimates in column (4) [(7)]. Diagnostic tests: *p*-values are reported. *CD-F* is Cragg and Donald's (1993) Wald F test statistic, Sargan-*p* is the *p*-value for Sargan's (1958) test for overidentifying restrictions ('na' implies exact identification) and RMSE is the root mean squared error.

Table 6. 2SLS results for the extended data set, 1984-2011

	Linear		Log	Linear			Log
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Log GDP per capita (PPP), 1984	–0.31		1.21***	–0.92			1.62***
	(0.89)		(0.40)	(1.05)			(0.56)
Average institutional quality, 1984-2011	0.19**		0.02	0.25***			–0.01
	(0.08)		(0.03)	(0.09)			(0.04)
RMSE	1.44		0.76	1.73			0.84
CD-F		5.99				1.99	
Sargan-p		Na		0.19			0.94
Reduced forms		*Inst*			*Inst*	*lnGDPpc*	
Log settler mortality	–0.83**	–4.31**	–0.11	–1.03***	–7.64***	–0.60***	–0.92***
	(0.37)	(1.76)	(0.15)	(0.31)	(1.30)	(0.10)	(0.22)
Log GDP per capita	1.21***	7.86***	1.41***				
	(0.27)	(1.80)	(0.21)				
British legal origin				–0.46	–4.92	–0.96***	–1.54***
				(0.35)	(3.44)	(0.20)	(0.53)
English language				4.58***	19.90***	1.83***	2.91***
				(1.30)	(6.05)	(0.39)	(0.62)
R^2	0.62	0.68	0.79	0.68	0.60	0.67	0.59
Norm-p	0.01	0.59	0.03	0.00	0.21	0.01	0.37
Hetero-p	0.00	0.18	0.00	0.00	0.21	0.75	0.04
HeteroX-p	0.00	0.29	0.00	0.00	0.18	0.78	0.05
RESET-p	0.00	0.00	0.49	0.00	0.29	0.12	0.07

Notes: Log denotes the natural log transformation of the dependent variable (capital inflows per capita); Linear denotes the dependent variable enters linearly. *Inst* and *lnGDPpc* denote the endogenous explanatory variables institutional quality and log of GDP per capita, respectively. All models include an intercept term. Diagnostic tests: *p*-values are reported. Robust standard errors are in parentheses; ***, ** and * denote statistical significance at the 1%, 5% and 10% levels, respectively. *N* = 45 for all regressions. The reduced forms in columns (1) and (2) [(2) and (3)] correspond to the 2SLS estimates in column (1) [(3)]; similarly, the reduced forms in columns (4), (5) and (6) [(5), (6) and (7)] correspond to the 2SLS estimates in column (4) [(7)]. Diagnostic tests: *p*-values are reported. *CD-F* is Cragg and Donald's (1993) Wald F test statistic, Sargan-*p* is the *p*-value for Sargan's (1958) test for overidentifying restrictions ('na' implies exact identification) and RMSE is the root mean squared error.

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(a) Histogram

(b) Plot against log(GDP per capita)

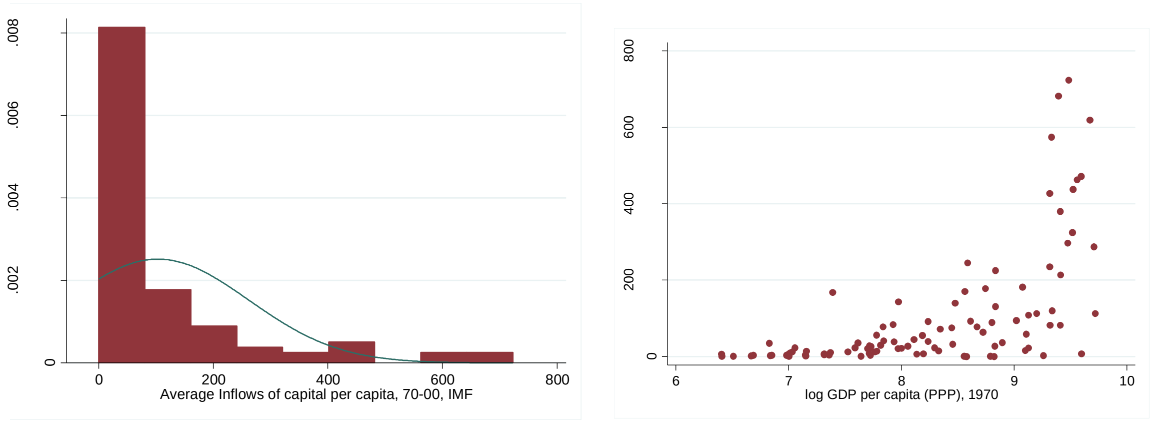

Figure 1. Average per capita inflows, 1970-2000

(a) Histogram

(b) Plot against log(GDP per capita)

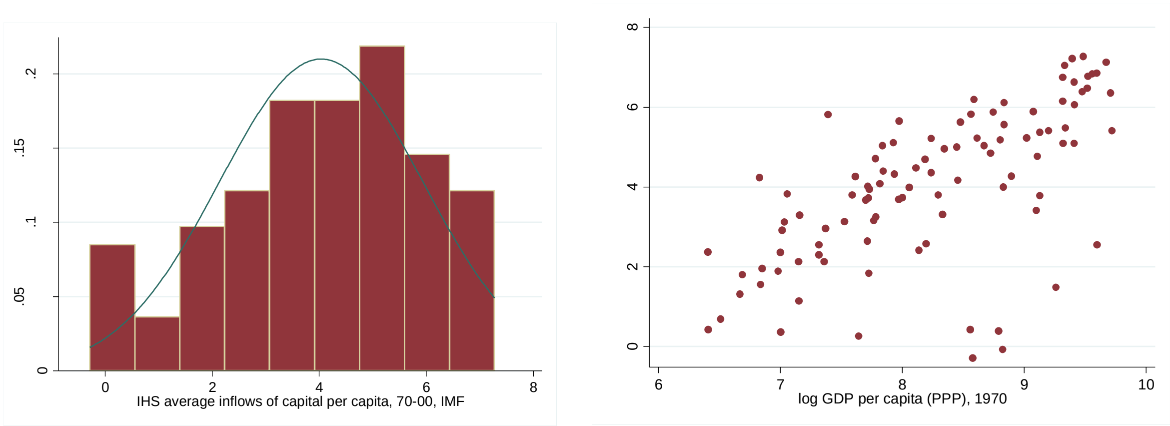

Figure 2. Inverse hyperbolic sine transformation, average per capita inflows, 1970-2000

(a) Plot of residuals for Table 1, column (2) (b) Plot of residuals for Table 1, column (4)

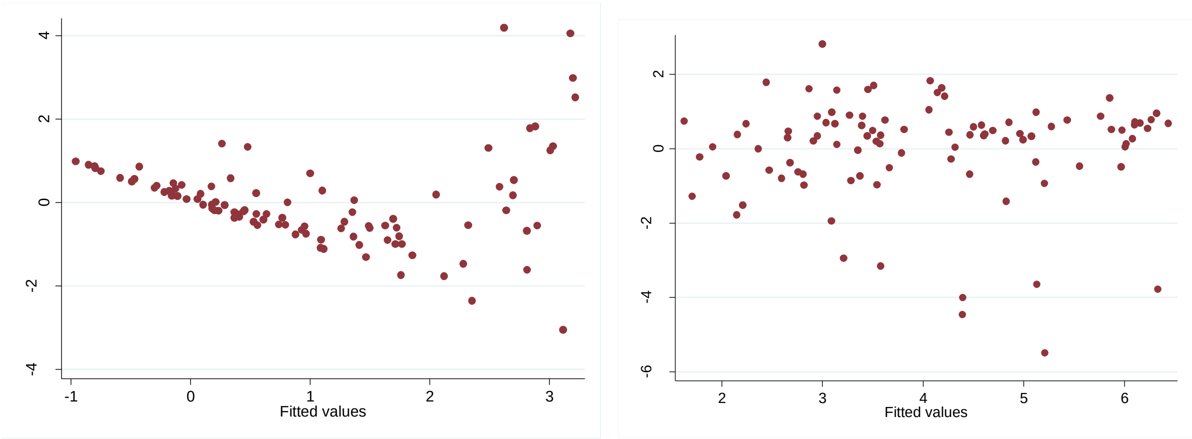

Figure 3: Heteroskedasticity of Residuals: 1970-2000

Appendix A

Table A1. Replication of AKV's Table 4

	Whole World Linear (1)	Whole World Linear (2)	Whole World Linear (3)	Base Sample Linear (4)	Base Sample Linear (5)	Base Sample Linear (6)	Base Sample Linear (7)	Base Sample Linear (8)
Log GDP per capita (PPP) 1970	1.12***	0.99***	0.82***	1.14***	1.11***	0.91***	0.13	
	(0.24)	(0.17)	(0.14)	(0.24)	(0.19)	(0.16)	(0.19)	
Log GDP per capita ($1996) 1970								0.21
								(0.16)
Average institutional quality,1984-2000							0.65***	0.59***
							(0.16)	(0.14)
Log average schooling, 1970-2000	0.09			0.06			–0.10	–0.19
	(0.18)			(0.18)			(0.15)	(0.20)
Log average distantness		–0.68			–0.58		–0.29	–0.28
		(0.71)			(0.73)		(0.60)	(0.60)
Average restrictions to capital mobility			–1.54***			–1.83***	–1.23**	–1.18**
			(0.53)			(0.61)	(0.48)	(0.46)
R^2	0.39	0.38	0.42	0.39	0.39	0.45	0.55	0.55
Observations	82	97	97	81	81	81	81	81
Norm-p	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Hetero-p	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
HeteroX-p	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
RESET-p	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
RMSE	1.34	1.26	1.22	1.35	1.34	1.28	1.18	1.18

Notes: Linear denotes the dependent variable enters linearly. All models include an intercept term. Diagnostic tests: *p*-values are reported. Robust standard errors are in parentheses; ***, ** and * denote statistical significance at the 1%, 5% and 10% levels, respectively.

Appendix B

Sample of 98 Countries in the extended dataset

Albania, Algeria, Angola, Argentina, Armenia, Australia, Austria, Azerbaijan, Bangladesh, Belarus, Bolivia, Brazil, Bulgaria, Burkina Faso, Canada, Chile, Colombia, Congo, Costa Rica, Côte d'Ivoire, Croatia, Cyprus, Czech Republic, Denmark, Dominican Republic, Ecuador, Egypt, El Salvador, Estonia, Ethiopia, Finland, France, Gabon, Gambia, Germany, Ghana, Greece, Guatemala, Guinea, Guyana, Haiti, Honduras, Hungary, India, Indonesia, Iran, Israel, Italy, Jamaica, Japan, Jordan, Kazakhstan, Kenya, Korea, Latvia, Lithuania, Madagascar, Malaysia, Mali, Mexico, Morocco, Mozambique, Namibia, Netherlands, New Zealand, Nicaragua, Niger, Nigeria, Norway, Oman, Pakistan, Panama, Papua New Guinea, Paraguay, Peru, Philippines, Portugal, Russia, Saudi Arabia, Senegal, Sierra Leone, Singapore, Slovenia, South Africa, Spain, Sweden, Trinidad and Tobago, Tunisia, Turkey, Uganda, Ukraine, United Kingdom, United States, Uruguay, Vietnam, Zambia, Zimbabwe.