Determinants of Capital Inflows: New Empirical Evidence

Introduction

The simplest benchmark neoclassical growth model (e.g. Solow, 1956) suggests that capital should flow from capital-rich developed countries to capital-poor developing countries as a result of 'diminishing returns to capital'. Lucas (1990) points out in his classic article that neoclassical assumptions on technology and trade in goods and factors are 'drastically wrong' and poses the provocative question "Why Doesn't Capital Flow from Rich to Poor Countries?" (Lucas 1990, p. 92). This puzzle, known as the 'Lucas Paradox'-the lack of capital flows from rich to poor countries-, introduced a new debate and spawned an extensive literature. From Lucas's point of view, differences in 'fundamentals', such as human capital between rich and poor countries potentially explain this paradox. Lucas rejects capital market imperfection or political risk as an explanation for the lower capital flows to poor countries, pointing to the fact that before World War II many of today's poor countries were colonies and subject to rich countries laws and governing institutions.

Empirical investigations of the Lucas paradox draw dramatically different conclusions concerning its key determinants. However, these alternative explanations of the Lucas paradox based on empirical models that focus on fairly narrow channels of the determinants of capital inflows, and in some cases model misspecification is partially responsible for inconclusive findings. For example, Alfaro, Kalemli-Ozcan, and Volosovych (2008) claim to provide a definite answer to this paradox and conclude that, differences in institutional quality determine capital inflows and can fully explain Lucas paradox. Papaioannou (2009) reaches a similar conclusion using bilateral bank inflows. Specific aspects of institutional quality have also been considered in the empirical literature, and economically significant barriers to foreign investment include government corruption (Wei, 2000) and default risk (Reinhart and Rogoff, 2004). However, Okada (2012) finds that institutional quality cannot independently provide an answer to the Lucas paradox when estimating a dynamic model; instead the interaction between institutional quality and financial openness can. Several other studies have also pointed to the importance of capital market frictions, such as capital controls as barriers to international capital movements (Henry, 2007; Abiad, Leigh, and Mody 2009; and Reinhardt, Ricci, and Tressel, 2013), as well as financial development (Forbes, 2010; Von Hagen and Zhang, 2010)[1]. Several other studies found that other types of frictions, such as information asymmetries matter for capital inflows (Portes and Rey, 2005; Hashimoto and Wacker, 2012). Finally, there is empirical evidence pointing to economic fundamentals as primary factors in explaining international capital

[1] Additional evidence that financial frictions matter more generally is offered by Kalemli-Ozcan et al. (2010), who estimate a simple version of the standard neoclassical open economy model using within country capital flow data for US states. They find that capital flows from slow-growing to fast-growing states, in line with the theory, and that the simple model explains a large proportion of within country variation, suggesting that barriers at the border that prevent international capital flows.

flows. Clemens and Williamson (2004), for example, study the first era of financial integration (1870-1913), examining British capital flows to 34 capital recipients, and find countries with higher average schooling, urbanization, and migration rates attract more foreign capital. By contrast, Gourinchas and Jeanne (2013) find faster productivity growth negatively affects capital inflows, meaning that capital does not flow to high-growth countries, a finding opposite to the neoclassical prediction.

In this paper, we empirically examine the relative importance of factors from all three broad categories (institutions, frictions, and fundamentals) in explaining Lucas' paradox.[2] Specifically, in modelling international capital flows, we consider a variety of potential determinants spanning all categories and, by examining the statistical significance of economic development in all models, we ask: which combinations of factors account for the Lucas paradox- the positive correlation between economic development and capital inflows? We find there is no magic bullet solution to the Lucas paradox, although this is often claimed in the empirical literature. Initial economic development (measured by log initial GDP per capita) is driving force of capital inflows in all models. Stocks of human capital, institutional qualities, and financial openness are also statistically significant determinants. However, none of these determinants can independently fully account for the positive relationship between economic development and capital inflows.

This paper is organized as follows. Section II reviews the determinants of capital inflows in the standard neoclassical model. Section III replicates closely related empirical work and points to the limitations of the models used. Section IV re-specifies the empirical model and produces new empirical findings using an updated dataset. Section V concludes.

Section II

Background

Theoretical issues: Before discussing the empirical specifications, we review the standard neoclassical model and show how differences in fundamentals, institutions, and frictions in the financial sector are represented in such a model. Consider a small open economy that uses capital *(K)* and labour *(L)* to produce output *(Y)* with constant returns to scale. For simplicity, we start from the production function:

$$Y = F(K, L) \tag{1}$$

[2] As some observed factors do not fit neatly into a single category, this categorization is not mutually exclusive.

The per capita production function from equation (1), including a technology parameter or shift parameter (A) that represents total factor productivity, can be expressed as follows:

$$\frac{Y}{L} = A\,F\left(\frac{K}{L}, \frac{L}{L}\right) \tag{2}$$

$$y = A\,f(k) \tag{3}$$

Where, lower case letters denote quantities per capita. Consider two countries *i* and *j* where, *i≠j* and the marginal products of capital are equal to the returns to capital *(r)* in each country:

$$\frac{dy_i}{dk_i} = A\,f'(k_i) = A\,r_i \tag{4}$$

$$\frac{dy_j}{dk_j} = A\,f'\left(k_j\right) = A\,r_j \tag{5}$$

Neoclassical theory suggests that capital should flow from capital-abundant countries to capital-scarce countries, based on diminishing returns to capital, before equalization takes place. In this set-up, consider the case where the marginal productivity of capital is higher in country *i* (capital-scare) than in country *j* (capital-abundant). Assuming that capital is perfectly mobile across countries, capital flows from country *j* to country *i* and the returns to capital are equalized with the global risk-free rate of return (*r*) implying that: $r_i = r_j = r_t$

In a panel set up, we can write this equation:

$$A_t f'(k_{it}) = r_t = A_t f'(k_{jt}) \tag{6}$$

However, there are other factors, such as 'human capital stock'(represented here by human capital per capita, *h*) (e.g. Lucas, 1990), differences in institutional quality (θ) (e.g. Alfaro et al., 2008), and frictions in capital markets (τ) (e.g. Reinhardt et al., 2013) that constitute a wedge between expected and ex-post returns to capital and influence this equality condition. If we incorporate these inputs and capital market imperfections in the neoclassical model the counterpart of equation (6) can be expressed as, similar to Alfaro et al.'s (2008) equation (5):

$$A_t\big(1-(h_{it}+\tau_{it}+\theta_{it})\big)f'(k_{it}) = r_t = A_t(1-\left(h_{jt}+\tau_{jt}+\theta_{jt}\right))f'\left(k_{jt}\right) \tag{7}$$

Equation (7) suggests the ex-post returns to capital are adjusted for the human capital stock, institutional quality, and capital market imperfections. In particular, a higher stock of human capital raises the marginal productivity of capital, a lower level of institutional quality, for example due to expropriation risk and/or higher corruption reduces the marginal productivity of capital, and a higher level of restrictions on capital movements causes an inefficient allocation and increases the cost of capital and reduces the marginal productivity of capital. In the existing empirical literature, the effects of these inputs (human capital stock or institutional quality) and/or restrictions on capital movements are examined to identify the determinants of capital inflows. The following sections critically examine the empirical studies closely related to our own, replicate and revise them in order to address their limitations, and produce new empirical findings using an updated dataset.

Section III

Does institutional quality explain the Lucas paradox?

Alfaro et al. (2008) investigate the determinants of capital flows from 1970 to 2000. They provide empirical evidence of the 'Lucas paradox' and show that differences in institutional qualities between the rich and poor countries help to explain the Lucas paradox. In particular, their main argument is that the positive and significant correlation between per capita income and per capital inflows disappears if an institutions index is included in the regression model (column 2 in Table 1). Alfaro et al. (2008) use cross-section OLS as they argue that most of the explanatory variables in their model are slowly changing over time; in particular, their main variable of interest, an institutions index (the International Country Risk Guide's measure of institutions index), shows almost no time variation during the sample period.

The basic specification of their empirical model is:

$$F_i = \mu + \alpha log Y_i + \beta I_i + \gamma X_i + \varepsilon_i \qquad (8)$$

where *F*, average inflows of direct and portfolio equity investment (per capita inflows), is a functions of the log of initial GDP per capita (*Y*), the institutions index (*I*), and controls (*X*). Detailed descriptions of sources of data on the variables used in this paper are given in the appendix (see, Appendix C). We proceed to standard diagnostic checking of their results and find their findings are not entirely convincing. Firstly, a histogram plot reveals that their dependent variable is highly skewed (Figure 1a) and has a long right tail. Transforming a highly skewed variable can often produce a relatively more symmetric distribution and, in this particular case, we log-transformed the dependent variable, per capita inflows.[3] A logarithmic transformation is often employed to obtain a more homogenous variance of the variable of interest and increases the forecast precision (Lutkepohl and Xu, 2009). Following this argument, we find a log-transformed version of their dependent variable is much more symmetric and more closely approximates a normal distribution (Figure 1b). We then replicate Alfaro et al.'s cross-section OLS results with the log-transformed dependent

[3] We follow a log-transformation method that is used in Busse and Hefeker (2007): $y = \log(x + \sqrt{(x^2 + 1)})$. See details in Appendix B.

variable using the authors' dataset, and find mixed results.[4] We reproduce their regression Tables 3 and 4 and compare our estimates of the log-transformed model (equation 9) with Alfaro et al.'s (2008) estimates.

$$\log(F_i) = \mu + \alpha log Y_i + \beta I_i + \gamma X_i + \varepsilon_i \tag{9}$$

Table 1 (corresponding to Alfaro et al.'s Table 3), column (2) shows that inclusion of an index of institutions fully explains the Lucas paradox, meaning that positive and statistically significant effect of GDP per capita becomes insignificant after inclusion of institutional quality in the model. However, we find inclusion of the institutions index does not change the statistical significance of GDP per capita if we use the log-transformed model, meaning that inclusion of the institutions index can no longer solve the Lucas puzzle of uphill capital flows (Column 2*). Moreover, the estimates of Alfaro et al.'s untransformed model are sensitive to outliers.[5] In particular, if we run their model removing five outlier observations (Sweden (SWE), Denmark (DNK), Finland (FIN), Great Britain (GBR), and Netherlands (NLD) out of their 98-country whole world sample), we find GDP per capita retains its statistical significance after controlling for the index of institutions (Column 2').[6]

We reach the same conclusion for Alfaro et al.'s Base sample (Columns 3 to 7 in Table 1), i.e., inclusion of the index of institutions does not solve the Lucas puzzle in their Base sample of 81 countries. In particular, the log-transformation for the Base sample (e.g., model 4*) gives the same result as model 2**. If we use the WDI's GDP per capita, the log-model for the Base sample (7*) gives the same result as model 2* even if we do not remove the outliers. Note that, columns (6) and (7) in Table 1 cannot reproduce Alfaro et al.'s estimates, which may suggest typos in their reported estimates.

A critical point is then to determine whether our log-model is a more appropriate specification than the level-log specification employed in Alfaro et al. (2008). We can see that the untransformed dependent variable used by Alfaro et al. is highly skewed (Figure 1a) compared to the log-transformed dependent variable (Figure 1b); however, the residuals (from model 2 in Table 1) appear to be approximately normally distributed based on inspection of figure 2a. To dig a bit deeper into why the residual plot of the untransformed model used by Alfaro et al. looks normal, we suspect the outlier observations in their sample may have contributed to this finding. The influence of these outliers on the residuals emerges as we plot residuals (Figure 2b) from the fitted regression column 2'

[4] We are grateful to the authors for sharing their dataset.
[5] Outlier observations have large residuals. To identifying outliers, we use studentized residuals. The studentized residual plot shows that there are 5 outliers and sorting the 10 largest and the 10 smallest residuals, we find the residuals of SWE exceeds -2.5 and those of FIN, DNK, NLD, and GBR exceed 2.5.
[6] As with Alfaro et al., the 98-country Whole World Sample includes all countries with data available for per capita inflows, GDP per capita, and index of institutions and excludes countries with population less than a million. The base sample is composed of 81 countries out of 98 countries for which all the main explanatory variables are available.

in Table 1. Excluding these outliers, the apparent residual normality of their untransformed model is largely reduced (Figure 2b).

We conduct formal diagnostic tests for normality, homoscedasticity, and functional form to test whether Alfaro et al.'s untransformed model or the log model better fit the data, by examining which of the two alternative specifications is closer to satisfying the underlying assumptions of statistical adequacy.[7] We find our preferred log-transformed model (model 2*) satisfies more of the formal diagnostic tests but still has a problem with residual non-normality. However, the fitted model performs better with respect to the diagnostic tests if we remove eight outliers (Singapore, South Africa, Trinidad and Tobago, Ukraine, Senegal, Iran, and Zimbabwe) from the log-transformed model (model 2** and residual plot 2c).[8] Moreover, a graphical presentation of heteroscedasticity tests of the estimated regressions also suggests that the log-transformed model better fits the data. A model with homoscedastic errors should not show any pattern to the residuals plotted against fitted values. The plotted residuals from our log-transformed model against fitted values (Figure 3b) show that there is no such pattern, whereas in Alfaro et al.'s model (Figure 3a), the residuals are more widely spread at higher fitted values. Alfaro et al. use White's heteroscedasticity-corrected standard errors to treat the symptoms of the problem; however, this cannot solve the underlying problem if heteroscedasticity is due to model misspecification. Moreover, we find there is a larger difference between robust and conventional standard errors if we use Alfaro et al.'s model.[9] However, the standard errors are almost the same in the log-transformed model. In particular, for the coefficient of GDP per capita, conventional standard errors (.20) are almost twice as large as robust standard errors (.13) in Alfaro et al.'s model (i.e., model 2) whereas they are 0.25 and 0.27 respectively in the log-transformed model (i.e., model 2*). This difference between conventional and robust standard errors also lends supports to model misspecification if we use the untransformed model.

Table 2 replicates Alfaro et al.'s Table 4 and examines other proposed explanations of the Lucas paradox, such as years of schooling, distantness, and capital controls.[10] We reach to the same conclusion for their full model, meaning that the log-model finds institutions cannot solve the Lucas paradox. In particular, among the alternative explanations of the Lucas paradox, only capital account restrictions variable is statistically significant and has a negative impact on capital inflows in the untransformed model. On the contrary, in addition to GDP per capita and institutional quality, years

[7] See details of the diagnostic tests in the Appendix B.

[8] Outliers of the log model are also identified by using studentized residuals and are required to remove all observations that exceed +2 and -2; otherwise the estimates do not satisfy all required diagnostic tests.

[9] King and Roberts (2012) argue that difference between conventional and robust standard errors is a 'bright red flag' of model misspecification.

[10] The Barro and Lee (2012) data set provides schooling data for 82 countries out of Alfaro et al.'s 98 country sample, although Alfaro et al., report that N=92 in their Table 4. Alfaro et al.'s own data set also contains schooling data for only 82 countries.

of schooling (i.e., human capital) is a statistically significant determinant and increases capital inflows, while restrictions to capital account is statistically insignificant in the log-transformed model. Our preferred specification for their full model also confirms that institutions cannot solve the Lucas paradox even after including these additional controls. However, to pass the diagnostic tests we need to remove the outliers in the full model (model 7* and 8* in Table 2) and the model excluding outliers also confirms that institutions cannot solve the Lucas paradox.

Alfaro et al. (2008, p.355) argue that "....[r]ecent research on institutions and development shows that these two variables are highly collinear because the historically determined component of institutions is a very good predictor for income in 1970. Nevertheless, our index of institutions is significant at the 1% level, while the log GDP per capita is not". On the contrary, we conclude that the statistical insignificance of GDP per capita is due to model misspecification or is dependent on outliers.

Azemar and Desbordes (AD) (2013) have also replicated Alfaro et al. and reached a similar conclusion. However, our analysis differs in several ways from AD. For example, we replicate Alfaro et al. using the authors' original data set and show how Alfaro et al.'s estimates are changed with alternative specifications. Alfaro et al. use the IMF's IFS capital flow data for their main analysis and also use Lane and Milesi-Ferretti's (hereafter, LM) (2007, updated 2012) capital stock data for robustness checking whereas AD's analysis is based solely on the LM data. AD use a different method (S-estimator by Verdi and Croux, 2009) to identify outlier observations and find six outliers: Botswana, India, Kuwait, Panama, Singapore, and Zimbabwe for the LM data. Our studentized residual test using the authors' original IFS data suggests the outlier observations are Sweden (SWE), Denmark (DNK), Netherlands (NLD), Great Britain (GBR), and Finland (FIN) for the untransformed model. AD's choice of preferred models is based purely on goodness-of-fit. Unlike AD, we focus on diagnostic testing of normality, homoscedasticity, and functional form for Alfaro et al.'s estimates and for the estimates of our preferred model. More importantly, a basic difference between our exercise and that of AD is a difference in motivation. Our main goal is to find a more general empirical model of the determinants of capital inflows. In doing so, this paper is a part of a main project that also replicates other closely related studies, revises these models, uses alternative econometric approaches (e.g. Fixed effects estimates and/or interaction model), and searches for an encompassing general model on the determinants of capital inflows.

Section IV

Determinants of capital inflows: new empirical findings

We examine the determinants of capital inflows using an updated dataset from 1984 to 2011 for Alfaro et al.'s whole world sample. We run cross-section OLS on the log-transformed model and compare the results with Alfaro et al. as a benchmark. Our preferred sample period (1984 to 2011) is not having missing observations of annual data for the institutions index for this full period, the main variable of interest. In comparison, Alfaro et al.'s sample period is from 1970 to 2000 whereas the ICRG's institutions index is available only from 1984. Alfaro et al.'s estimates are based solely on ICRG's index of institutions, whereas other indices are often used to measure institutional quality, such as the Freedom House Index, Transparency International's CPI (corruption perception index), World Bank's CPIA (Country policy and institutions assessments) index, and the World Bank Institute's Governance Indicators (Kaufmann et al., 1996, updated 2011). We argue that a perfect institutions index will undoubtedly never exist and we acknowledge the complexities of using such indices for cross-country comparisons suggesting us to use an alternative measure of institutional quality to examine whether our findings are robust. Therefore, we also use the WBI's governance index in addition to the ICRG's institutions index.

Table 3 provides results consistent with our findings using the authors' dataset and suggests that the index of institutions solves the Lucas paradox only if the dependent variable is not log-transformed (column (2) in Table 3). By contrast, the index of institutions cannot fully explain the Lucas paradox and per capital income retains a positive and statistically significant effect on capital inflows in the log-transformed model (column (3) in Table 3). We also consider an alternative measure of institutional quality – the WBI's governance indicator. Interestingly, we find that the index of institutional quality cannot solve the Lucas paradox when this alternative measure is used, even when the dependent variable is not log-transformed (column (4) in Table 3). In the log-transformed model (column (5) in Table 3), the evidence of the Lucas paradox is even stronger in the sense that the statistical significance of the coefficient of GDP per capita is stronger. Column (6) in Table 3 adds additional control variables proposed by Alfaro et al. and finds the paradox does not go away. If we add other standard determinants of capital inflows the Lucas paradox remains pertinent. In particular, we examine other commonly used determinants of capital inflows in the literature, such as trade openness, financial development, and macroeconomic stability (measured by inflation) and find the Lucas paradox still persists (columns 7-9 in Table 3). These findings suggest that the misspecification in Alfaro et al.'s model appears to have carried over the updated sample period.

To determine whether our log model is a better fit for the data than the linear specification employed in Alfaro et al., (2008), we check formal diagnostic tests and plot residual normality of the estimated regressions for the two alternative specifications, a similar exercise to that performed for the Alfaro et al. replication. The density plots of the residuals (Figure 5) indicate that the log model (Figure 5b) is closer to having normally distributed residuals and the residuals from the linear model (Figure 5a) appear to depart from the normality assumption to a much greater extent, thus suggesting the log model is closer to satisfying the underlying assumptions of statistical adequacy. Formal diagnostic tests, such as normality, homoscedasticity, and functional form for the two alternative specifications for each estimated regression are reported in the last rows of Table 3. Model (8) in Table 3, which utilizes the maximum number of observations (due to dropping schooling), gives us a preferred model compared to Model (7) in terms of its residual normality plot (Figure 5c) and the results of the formal diagnostic tests. The majority of the tests are satisfied for the log models suggesting that the log models are a better fit for the data than the untransformed model. Moreover, we find a larger difference between robust and conventional standard errors if we use untransformed model. In particular, for the coefficient of GDP per capita, conventional standard errors (.59) are almost three times larger than robust standard errors (0.27) in the untransformed model (model (2) in Table 3) whereas there is little difference between the conventional and robust standard errors in our preferred log transformed model (model (3) in Table 3). This difference between conventional and robust standard errors also lends supports to model misspecification if we use the untransformed model. A concern of the diagnostic tests is that our preferred log transformation does not satisfy the functional form test (Ramsey RESET test) whereas a simple log transformation (model 9 in Table 3) does. However, residual plot from model (8) that uses our preferred log transformation is more closely normally distributed than that of model (9) that uses a simple log transformation, suggesting that the BH log-transformation better fits the data. We also examine the distributions of per capita inflows and log-per capita inflows for the updated data and again find that the log-transformed per capita inflows (Figure 4b) are closer to being normally distributed than the untransformed per capita inflows (Figure 4a).

Multicollinearity test using Frisch-Waugh theorem

The high correlation between GDP per capita and institutional quality that can make the regression results spurious. In particular, a higher level of institutional quality has a direct effect on capital inflows and GDP per capita also depends on institutional quality suggesting an indirect effect of GDP per capita on capital inflows. Given a high correlation (0.82) between GDP per capita and institutional quality, it may be difficult to identify individual effect of GDP per capita or institutional quality on capital inflows from a multiple regression. We apply Frisch-Waugh theorem to examine whether the coefficients the two variables from a univariate regression is exactly the same from the multiple regressions. To identify individual effect of GDP per capita, we plot residuals from the regression of per capita inflows on average institutional quality against the residuals from the regression of log GDP per capita 1984 on average institutional quality (Figure 6a). The slope coefficient of the fitted line is 0.24 is the same coefficient for GDP per capita we found in column 3 Table (3). Similarly, we plot residuals from the regression of per capita inflows on GDP per capita against the residuals from the regression of GDP per capita on average institutional quality and identify individual effect of institutional quality (Figure 6b). The slope coefficient of the fitted line is 0.05 that is the same coefficient of institutional quality in the multiple regressions in column 3 in Table (3). From the slope coefficients of this exercise also suggest us that, capital flows for the sample of countries during 1984-2011 are largely driven by initial economic development, and in contrast to Alfaro et al. (2008), not solely by countries institutional quality index.

Table 4 includes two additional controls suggested as potential determinants of capital inflows by standard open economy neoclassical model: initial capital stock and total factor productivity. When total factor productivity (TFP) alone is included as explanatory variable, insignificance of GDP per capita (Column 1 in Table 4) reflects the high correlation (0.88) between log GDP per capita and log TFP, as is expected. Column (2) adds initial capital stock per worker as an additional control and finds the effects of GDP per capita on capital inflow is also weaker in terms of statistical significance. Column (3) includes other standard controls along with TFP and the initial capital stock per worker and finds that the Lucas paradox disappears. However, observations of these models are reduced to 69 due to the unavailability of schooling and capital stock data. If we drop TFP and add initial capital stock to our preferred controls (Column (4) in Table 4), we find capital flows to low income countries. But the finding is statistically insignificant. Therefore, inclusion of TFP and initial capital stock give results that are rather sensitive to inclusion of other controls and are based on a relatively smaller number of observations. And although GDP per capita is no longer statistically significant when TFP is included, as is well known TFP captures a host of unobservable factors related to income, including factors related to institutional quality, and in this sense TFP cannot 'explain' Lucas paradox.

Robustness Checks

Table 5 repeats the same exercise but uses an alternative source of capital inflows: the LM capital inflows data (Lane and Melesi-Ferretti, 2007, updated 2012) obtained by first differencing the stock data of LM.[11] An issue with using the IMF's IFS capital flow data is that it does not incorporate potentially large valuation effects. Capital stock data measure of the long-run asset holding positions of a country and LM's estimates adjust for the valuation effects of capital. Column (1) demonstrates that the Lucas paradox exists but it disappears in column (2) if an index of institutional quality is included in the model. However, GDP per capita retains its statistical significance in the log transformed model in column (3) indicating that our findings are robust to the use of alternative sources of capital data. This finding is also robust to other proposed explanations of the Lucas paradox as shown in column (4). The full model with log-transformation (column (4)) is closer to satisfying the underlying assumptions of statistical adequacy. We can compare the results from this

[11] The LM data source is an alternative source of capital flow data for robustness checking of our estimates from the IMF capital flow data.

table to AD's findings; for example, we run models (5) and (6) similar to AD's model (5') and (6') of their Table (4). Our findings also support their claim that the index of institutional quality cannot solve the Lucas paradox.

Table 6 adds extra controls that are commonly used in this literature to for the robustness checks. Column (1) investigates the effects of infrastructure measured by percentage of paved roads in total roads and finds a positive effect of this variable but insignificant.[12] We also examine the effects of capital market development and use stock market value over GDP.[13] Column (2) finds that market capitalization has an insignificant positive effect on capital inflows. We examine whether the tax heaven have significant effects on capital inflows and find that, taxes on profits, income and capital gains are negatively associated with capital inflows but again statistically insignificant.[14] Column (4) and (5) include an oil country dummy and a sub-Sahara country dummy but they also turns out as insignificant determinants of capital inflows. A note of this robustness checks is that, we do not see any change in terms of statistical significance and/or sing of our main variable of interests, GDP per capita and institutional quality index.

Section V

Conclusion

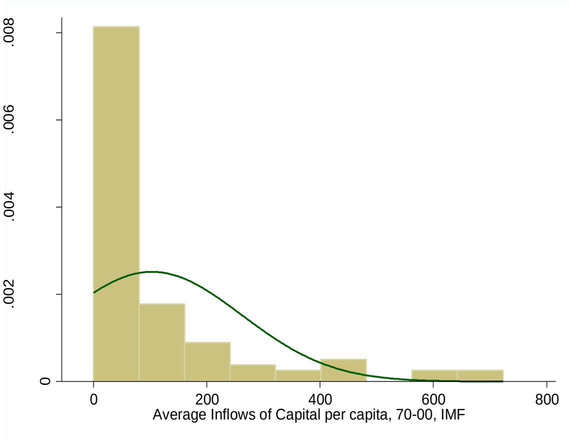
We observe that existing literature that identifies specific determinant of capital inflows and argue for a definitive explanation of the lack of capital flows from rich to poor countries however, the overall picture of this existing literature is inconclusive. We find a conclusive answer that, the mystery of the Lucas paradox still persists; specifically there is no single determinant that can fully capture the positive effects of economic development on capital inflows. In other words, we find initial economic development (i.e. initial GDP per capita) is the main driving force of capital inflows. We do not argue that institutional qualities are not important determinants; rather we argue that an index of institutions is not magic bullet solutions to the Lucas paradox. We confirm that our findings are based on the better fitting models and satisfy a standard set of diagnostic tests that is surprisingly missing in the existing literature. Moreover, our findings are based on the analysis of sample period covering more recent data and robust to alternative sources of capital flow data.

Appendix A: Graphs and Tables

[12] Alfaro et al. (2008) finds a positive but insignificant effect of infrastructure, measured by paved roads, on capital inflows.
[13] King and Levine (1993) argue that financial intermediation and financial development aid the efficient allocation of global capital.
[14] Gastanga et al (1998), Wei (2000) use tax rate as a determinant of FDI.

Figure 1: Histogram plots of the dependent variable (capital inflows): 1970-2000[15]

(a) Untransformed model



(b) Log-transformed model

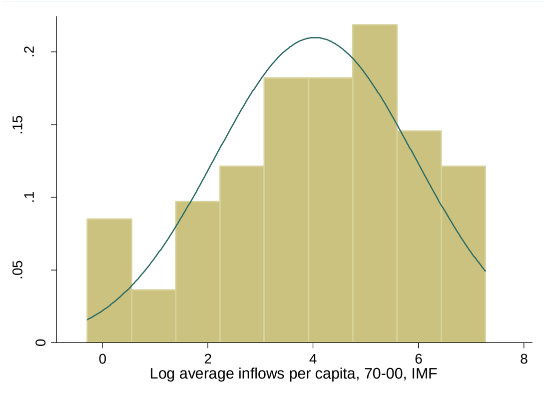
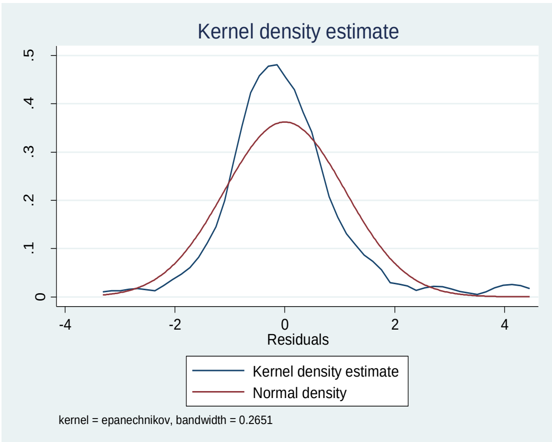
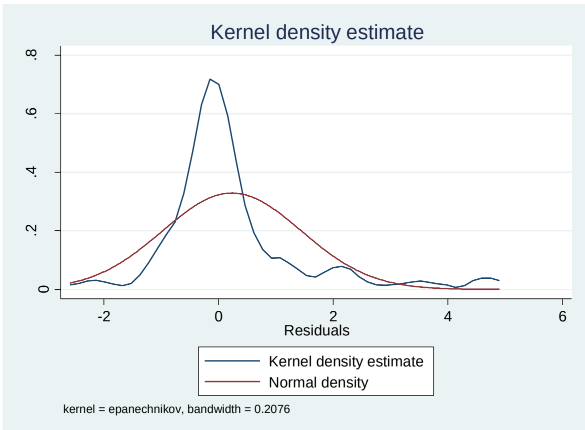


Figure 2: Kernel density and normal density of estimated residuals: 1970-2000

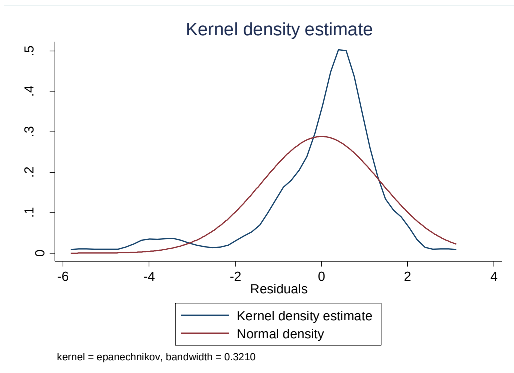
(a) Residuals of Alfaro et al.'s model



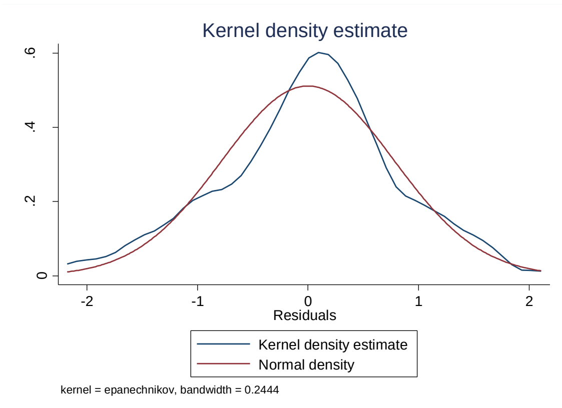
(b) Residuals of Alfaro et al.'s model excluding outliers



(c): Residuals of log-model including outliers



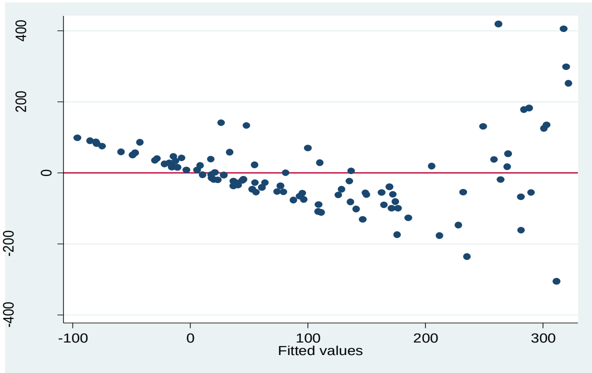
(d) Residuals of log-model excluding outliers



[15] Alfaro et al.'s (2008) original data set.

Figure 3: Heteroscedasticity of residuals: 1970-2000

(a) Plot of residuals for Alfaro et al.'s model



(b) Plot of residual for the log model

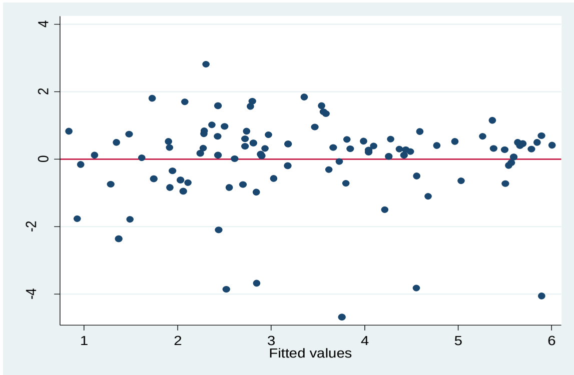
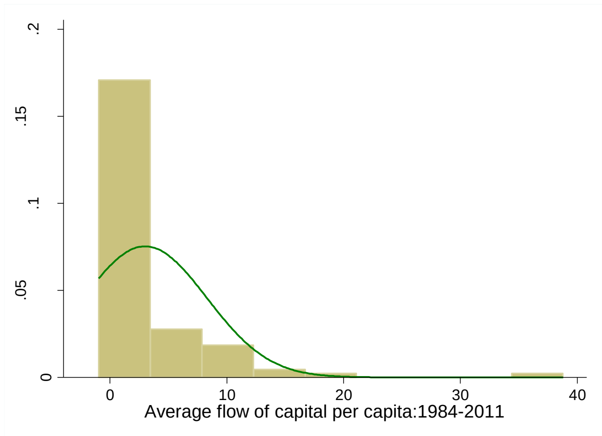


Figure 4: Histogram plots of the dependent variable (capital inflows): 1984-2011

(a) Untransformed model



(b) Log-transformed model

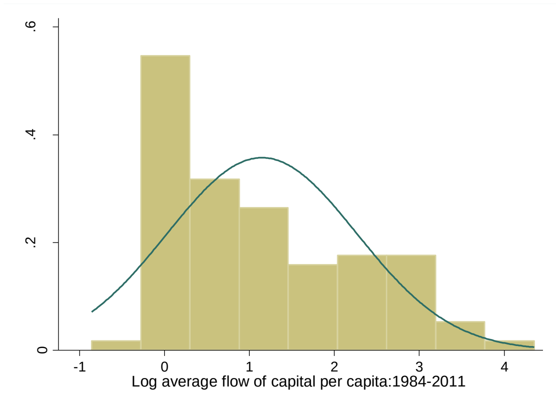
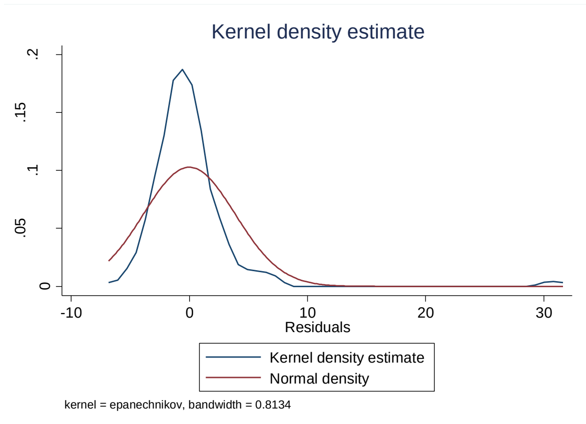
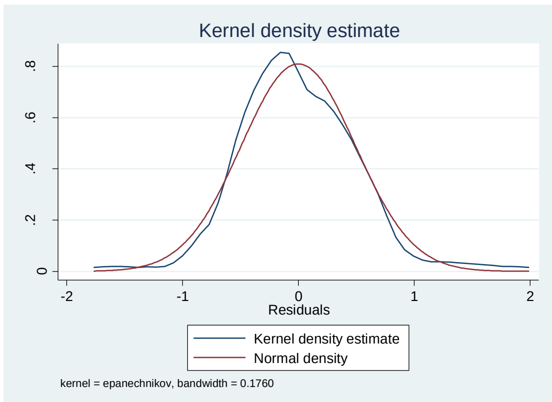


Figure 5: Kernel density and normal density of estimated residuals

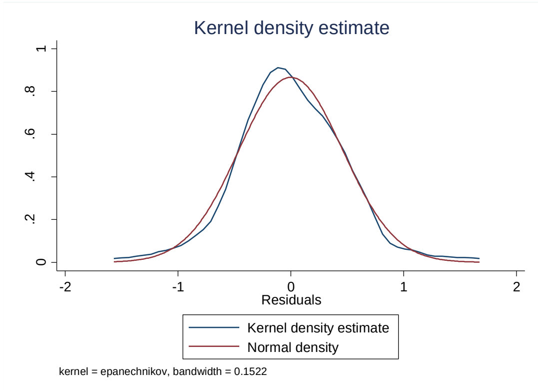
(a) Residuals of model 2 in Table (3)



(b) Residuals of model 3 in Table (3)



(c) Residuals of model 8 in Table (3)



(d) Residuals of model 9 in Table (3)

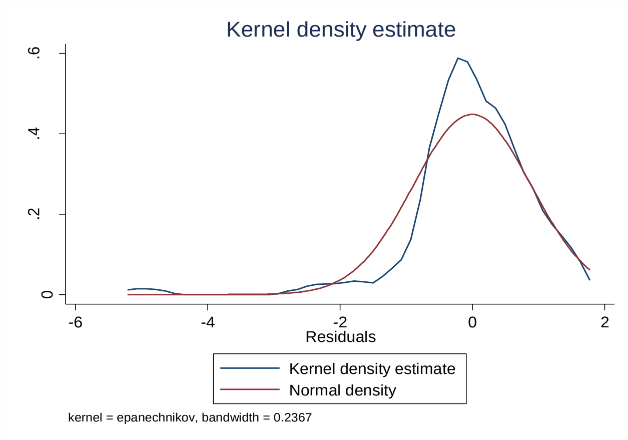


Figure 6a: Correlation of capital inflows per capita and log GDP per capita after controlling for institutional quality

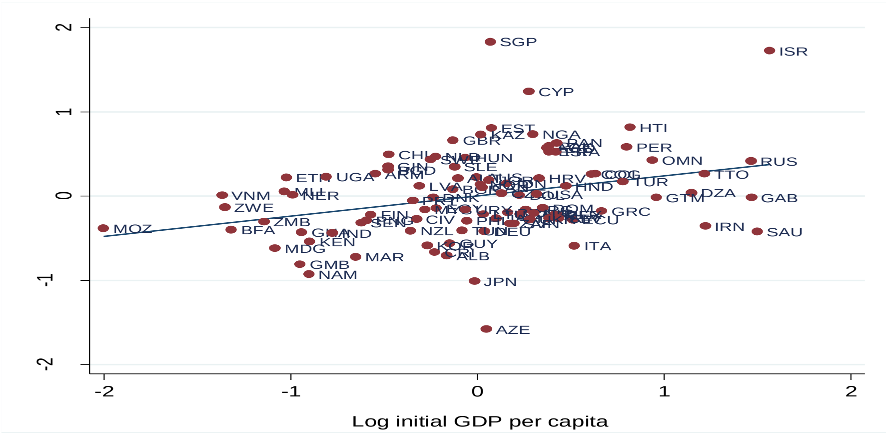


Figure 6b: Correlation of capital inflows per capita and institutional quality after controlling for log GDP per capita

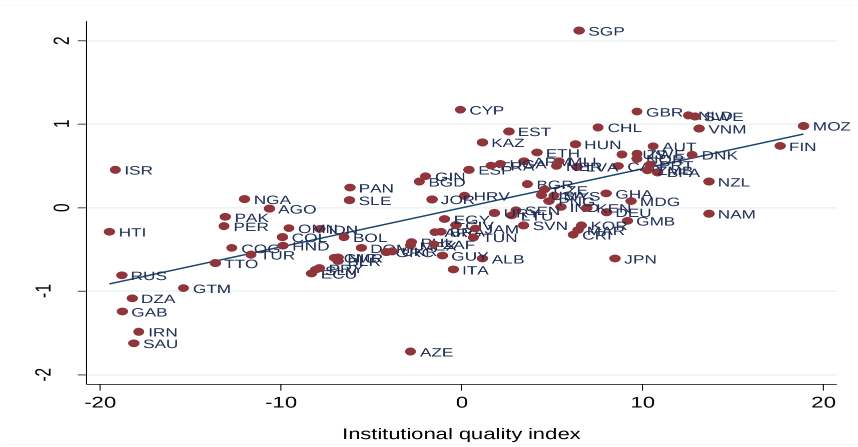


Table 1: Replication of Alfaro et al.'s Table 3, 1970-2000 (N=98 countries)

VARIABLES	(1) Whole World	(2) Whole World	(2*) Whole World	(2') Whole World	(2**) Whole World	(3) Base Sample	(4) Base Sample	(4*) Base Sample	(5) Base Sample	(6) Base Sample	(7) Base Sample	(7*) Base Sample
Log GDP pc (PPP) 1970	**1.05*** **	**0.20**	**0.69*** *	**0.24*** *	**0.97*** **	**1.18*** **	**0.14**	**0.85*** **				
	(0.17)	(0.13)	(0.27)	(0.11)	(0.18)	(0.19	(0.20)	(0.22)				
Log av GDP pc (PPP)										**0.84**	**0.20**	**0.49*** *
										(0.13)	(0.13)	**(.23)**
Av institutional quality,1984-2000		**0.68*** **	**0.51*** **	**0.49*** **	**0.47*** **		**0.75*** **	**0.51*** **	**0.82*** **		**0.67*** **	**0.47*** *
		(0.14)	(0.18)	(0.10)	(0.10)		((0.17)	(0.12)	(0.12)		(0.15)	(.23)
R-squared	0.37	0.52	0.47	0.54	0.78	0.39	0.52	0.81	0.52	0.44	0.53	0.46
Observations	98	98	98	93	90	81	81	73	81	81	81	81
Normality test:												
Doornik-Hansen	0.00	0.00	0.00	0.00	0.64	0.00	0.00	0.50	0.00	0.00	0.00	0.00
Shapiro-Wilk	0.00	0.00	0.00	0.00	0.28	0.00	0.00	0.11	0.00	0.00	0.00	0.00
Heteroscedasticity:												
White	0.00	0.00	0.74	0.00	0.17	0.00	0.00	0.18	0.00	0.00	0.00	0.77
Breusch-Pegan	0.00	0.00	0.36	0.00	0.02	0.00	0.00	0.16	0.00	0.00	0.00	0.36
RESET	0.00	0.00	0.62	0.00	0.08	0.00	0.00	0.03	0.00	0.00	0.00	0.73
RMSE	1.26	1.11	1.39	0.76	0.78	1.33	1.19	0.74	1.18	1.70	1.18	1.44

Notes: 2* and 7* use log (per capital inflows) as dependent variables, 2** uses log (per capita inflows) as dependent variable and removes outliers, 2' uses per capita inflows as dependent variable and removes outliers, and the other remaining models use per capital inflows as dependent variable. Robust standard errors are in parentheses, *** p<0.01, ** p<0.05, * p<0.1. Diagnostic tests: p-values are reported. See appendix C for detailed explanations of all variables and sources.

Table 2: Replication of Alfaro et al.'s Table 4, 1970-2000 (N=98 countries)

VARIABLES	(1) Whole World	(2) Whole World	(3) Whole World	(4) Base Sample	(5) Base Sample	(6) Base Sample	(7) Base Sample	(7*) Base Sample	(8) Base Sample	(8*) Base Sample
Log GDP pc (PPP) 1970	1.12***	0.99***	0.82***	1.14***	1.11***	0.91***	0.13	0.56**		
	(0.24)	(0.17)	(0.14)	(0.24)	(0.19)	(0.16)	(0.19)	(0.23)		
Log GDP pc ($1996) 1970									0.21	0.47***
									(0.16)	(0.16)
Av institutional quality,1984-2000							0.65***	0.48***	0.59***	0.43***
							(0.16)	(0.11)	(0.14)	(0.12)
Log average school 1970-2000	0.09			0.06			-0.10	0.47**	-0.19	0.40**
	(0.18)			(0.18)			(0.15)	(0.16)	(0.20)	(0.17)
Log average distantness		-0.68			-0.58		-0.29	0.50*	-0.28	0.48
		(0.71)			(0.73)		(0.60)	(0.30)	(0.60)	(0.30)
Average restrictions to capital mobility			-1.54***			-1.83***	-1.23**	-0.62	-1.18**	-0.60
			(0.53)			(0.61)	(0.48)	(0.41)	(0.46)	(0.37)
R-squared	0.39	0.38	0.42	0.39	0.39	0.45	0.54	0.83	0.55	0.84
Observations	82	97	97	81	81	81	81	73	81	73
Normality test: Doornik-Hansen	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.61	0.00	0.34
: Shapiro-Wilk	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.62	0.00	0.33
Heteroscedasticity: White's	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.05	0.01	0.15
Breusch-Pegan	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.29	0.00	0.42
RESET	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.31	0.00	0.23
RMSE	1.34	1.26	1.22	1.34	1.33	1.27	1.18	0.69	1.28	0.67

Note: 7* and 8* are the log-transformed model and excluding outliers. Robust standard errors are in parentheses, *** p<0.01, ** p<0.05, * p<0.1. Diagnostic tests: p-values are reported. See appendix C for detailed explanations of all variables and sources.

Table 3: OLS cross-section using new data, 1984-2011 (N=98 countries)

VARIABLES	(1) Linear	(2) Linear	(3) Log	(4) Linear	(5) Log	(6) Log	(7) Log	(8) Log	(9) Log
Log GDP pc (PPP) 1984	**2.58*** **	**0.30**	**0.24*** **	**0.37***	**0.27*** **	**0.18** **	**0.20** **	**0.18*** **	**0.64*** **
	(0.44)	(0.27)	(0.07)	(0.20)	(0.05)	(0.09)	(0.11)	(0.07)	(0.21)
Av inst quality,1984-2011		**0.20*** **	**0.05*** **			**0.04*** **	**0.04*** **	**0.04*** **	**0.06*** **
		(0.04)	(0.01)			(0.01)	(0.01)	(0.01)	(0.02)
Average governance index,1996-2011				**0.65*** **	**0.14*** **				
				(0.12)	(0.01)				
Average open to cap mobility						**0.09**	**0.08**	**0.09***	**0.03**
						(0.05)	(0.05)	(0.05)	(0.10)
Log average school 1985-2010						**0.07**	**0.01**		
						(0.14)	(0.16)		
Log average distantness						**-0.22**	**-0.20**	**-0.20**	**0.25**
						(0.20)	(0.21)	(0.20)	(0.32)
Log average trade							**0.19**	**0.18**	**0.72*** **
							(0.17)	(0.16)	(0.21)
Log average fin development							**0.14**	**0.18***	**0.02**
							(0.09)	(0.10)	(0.16)
Log average inflation							**0.03**	**0.03**	**-0.43*** **
							(0.05)	(0.04)	(0.10)
Observations	98	98	98	98	98	89	89	98	97
R-squared	0.34	0.46	0.81	0.51	0.84	0.83	0.84	0.83	0.80
Normality test: Doornik-Hansen	0.00	0.00	0.00	0.00	0.00	0.00	0.11	0.13	0.00
: Shapiro-Wilk	0.00	0.00	0.01	0.00	0.00	0.00	0.32	0.39	0.00
Heteroscedasticity:White	0.11	0.56	0.67	0.42	0.81	0.03	0.01	0.02	0.46
:Breusch-Pegan	0 .09	0.08	0.21	0.04	0.40	0.10	0.10	0.23	0.22
RESET	0.00	0.00	0.00	0.00	0.00	0.01	0.00	0.00	0.80
RMSE	4.34	3.92	0.50	3.74	0.44	0.47	0.46	0.48	0.92

Notes: Alfaro's whole world (98) country sample is used. Dependent variable is average capital inflows per capita for Models (1, 2, and 4) as used in Alfaro et al. (2008). Dependent variable is log of the average capital inflows per capita in models (3, 5, 6, 7, 8, and 9). Robust standard errors are in parentheses, *** p<0.01, ** p<0.05, * p<0.1 Diagnostic tests: p-values are reported for each corresponding test. See appendix C for detailed explanations of all variables and sources.

Table 4: OLS cross-section using new data, 1984-2011, (N=98 countries)

VARIABLES	(1)	(2)	(3)	(4)
Log GDP per capita (PPP),1984	0.21	0.51*	0.43	-0.09
	(0.16)	(0.27)	(0.31)	(0.16)
Average inst. quality,1984-2011	0.05***	0.05***	0.04***	0.04***
	(0.01)	(0.01)	(0.01)	(0.01)
Log average TFP	-0.04	-0.16	-0.18	
	(0.18)	(0.20)	(0.22)	
Log capital stock per work, 1984		-0.18	-0.11	0.18
		(0.11)	(0.14)	(0.11)
Av. openness to cap mobility			0.11*	0.13**
			(0.06)	(0.06)
Log average distantness			-0.20	-0.13
			(0.25)	(0.23)
Log average trade			0.28	0.28
			(0.19)	(0.18)
Log average fin development			0.15	0.17
			(0.11)	(0.10)
Log average inflation			-0.04	0.06
			(0.29)	(0.25)
Observations	69[a]	69	69	74[b]
R-squared	0.839	0.843	0.874	0.867
Normality test: Doornik-Hansen	0.00	0.00	0.09	0.44
: Shapiro-Wilk	0.01	0.00	0.16	0.65
Heteroscedasticity:White :Breusch-Pegan	0.41, 0.09	0.43,0.09	0.21, 0.10	0.07,0.22
RESET	0.09	0.10	0.01	0.00
RMSE	0.47	0.47	0.44	0.45

Notes: [a] sample of observations reduced to 69 due to missing data on schooling and TFP is calculated using schooling data, sample size of models 2 and 3 are also due to schooling and capital stock data, [b] Sample size increases to 74 as we drop TFP but still smaller observations due to missing data on capital stock. See appendix C for detailed explanations of all variables and sources.

Table 5: OLS regression using new data, 1984-2011 (N=98 countries): LM flow data

VARIABLES	(1)	(2)	(3) Log	(4) Log	(5) Log	(6) Log
Log GDP per capita (PPP),1984	**3.32*** **	**0.51**	**0.79*** **	**0.75*** **	**0.88*** **	**0.65*** **
	(0.66)	(0.32)	(0.12)	(0.13)	(0.11)	(0.16)
Average inst. Quality,1984-2011		**0.25*** **	**0.05*** **	**0.04*** **		
		(0.05)	(0.01)	(0.01)		
Av. openness to cap mobility				0.07		0.03
				(0.08)		(0.08)
Log average distantness				-0.04		-0.20
				(0.26)		(0.25)
Log average trade				0.72***		
				(0.16)		
Log average fin development				0.02		
				(0.13)		
Log average inflation				-0.02		
				(0.05)		
Average Governance index, 1996-2011					**0.14*** **	**0.15*** **
					(0.02)	(0.03)
Log average school 1985-2010						0.42**
						(0.21)
Observations	98	98	98	98	98	89
R-squared	0.28	0.38	0.83	0.87	0.83	0.84
Normality: Doornik-Hansen	0.00	0.00	0.00	0.00	0.00	0.00
Shapiro-Wilk	0.00	0.00	0.01	0.05	0.00	0.00
Hetero (White,	0.17	0.61	0.37	0.55	0.27	0.51
Breusch-Pegan)	0.13	0.10	0.15	0.01	0.09	0.07
RESET	0.00	0.00	0.33	0.75	0.28	0.04
RMSE	6.37	5.96	0.76	0.69	0.75	0.76

Robust standard errors are in parentheses, *** p<0.01, ** p<0.05, * p<0.1. Diagnostic tests: p-values are reported. See appendix C for detailed explanations of all variables and sources.

Table 6: Robustness Checks for OLS regressions: 98 countries: 1984-2011

	(1)	(2)	(3)	(4)	(5)
Log initial GDP per capita (PPP)	0.76***	0.84***	0.90***	0.85***	0.77***
	(0.12)	(0.17)	(0.14)	(0.12)	(0.15)
Index of institutions	0.05***	0.05***	0.05***	0.05***	0.05***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Paved roads	0.00				
	(0.00)				
Stock market value		0.00			
		(0.00)			
Tax on profits			-0.00		
			(0.00)		
Oil dummy				-0.35	
				(0.34)	
Sahara dummy					-0.09
					(0.29)
Observations	98	76	90	98	98
R-squared	0.834	0.811	0.833	0.834	0.833

Robust standard errors are in parentheses, *** p<0.01, ** p<0.05, * p<0.1. See appendix C for detailed explanation of all variables and sources.

Appendix B: further explanation to the footnotes

Log-transformation: We follow a log-transformation method used by Busse and Hefeker (2007) to deal with the countries with negative values of capital flows, which is similar to the problem of zero valued trade flows in Gravity models (e.g., Helpman et al., 2008). BH argue that this transformation maintains the sign of the variable of interest, does not reduce the number of observations, and the values of the variable pass from a linear scale at small absolute values to a logarithmic scale at large values. However, adding a small positive number (in this case, 1) is arbitrary and different positive numbers can give different values of the log-transformed variable. Flowerdew and Aitkin (1982) showed that small differences in the selected constant can distort the result seriously. Moreover, the log-model generates estimates of the log of capital inflows not of capital inflows and the antilogarithms of these estimates tend be biased (Haworth and Vincent, 1979). The concavity of the log function should create a downward bias when using OLS and the Jensen's inequality implies that $E(\ln(y) \neq \ln E(y)$. We acknowledge these drawbacks of log-transformation of our preferred model.

Diagnostic tests:

Normality: It tests whether the errors are identically and independently distributed, which is necessary for the hypothesis to be valid. Doornik-Hansen's (2008) test for normality is based on the skewness and kurtosis of the OLS residuals and is asymptotically distributed as chi-square (2) under the null of normality. We also use Shapiro-Wilk W test where the p-value is based on the assumption that the distribution is normal.

Homoscedasticity: Homoscedastic errors is one of the main assumptions of OLS regression. If the model is well fitted, there should not be any pattern to the residuals plotted against the fitted values. We employ two tests for homoscedasticity: the Breusch-Pegan (1980) test and the White's test (a special case of Breusch-Pegan test). P-value of the null hypothesis is based on the assumption that the variance of the residuals is homogenous.

Functional form: A model specification error can occur when one or more relevant variables are omitted or one or more irrelevant variables are included in the model. We use Ramsey RESET test (Stata's ovtest) that creates new variables based on the predictors and refits the model using those new variables to see if any of them would be significant. The p-value of the null hypothesis is based on the assumption that the model has no omitted variables.

RMSE (root mean square error): RMSE is frequently used as a measure of the difference between values predicted by a model or an estimator and the values actually observed. In other words, it is the standard deviation of the errors and measures the spread of the data around the regression line. The smaller the value of RMSE, the better the fitted line in terms of prediction.

Appendix C: Data descriptions and sources

Capital inflows per capita, 1984-2011: Sum of FDI (IFS line: BFDIA) and portfolio (IFS line: BFPLE) inflows (2013). The data is in current US dollars are deflated by US CPI with base year 2005=1 and divided by population.

Stocks of foreign capital (LM), 1984-2011: Foreign claims on domestic capital, from Lane and Milesi-Ferretti (2012). Capital inflows are obtained by the first difference of stock data of LM.

GDP per capita in 1984 in PPP dollars: GDP at PPP from Penn World Tables, Ver. 7.1, Heston, Summers, and Aten (2012), divided by population.

GDP per capita, 1984-2011 in constant 2005 dollars: GDP from WDI, World Bank (2012), divided by population.

Institutional Quality, 1984-2011: This is a composite index, which is the sum of yearly rating of the 12 components from International Country Risk Guide, the PRS Group (2012). To ensure the consistency of interpretation, each component of the index is rescaled, as follows, to range from 0 to 10. Thus, the theoretical range of this index is 0 to 120, where a higher score means institutional qualities are better and lower risks.

Governance Indicator, 1996-2011: Alternative measures of an institutions index. Composite indicator is the average of yearly rating of 5 indicators. Data are taken from Kaufmann et al., (2010, updated 2013).

Openness to capital mobility, 1984-2011: Measures a country's degree of capital account openness based on the IMF's Annual Report on Exchange Arrangements and Exchange Restrictions developed by Chinn and Ito (2006, 2012), where a higher index value indicates greater capital account openness. Values range from

2.6(most financially open) to -2.6 (least financially open). Unlike ours, for restrictions on capital mobility Alfaro et al. (2008) use the mean value of four dummy variables from IMF's Annual Report on Exchange Arrangements and Exchange Restrictions: exchange arrangements; payments restrictions for capital transactions, payments restrictions on payment for capital transactions; and surrender or repatriation requirements for export proceeds.

Schooling, 1985-2010 **:** Years of schooling of persons of age 25 or above is a measure of stock of human capital (h) at five-year intervals. Linear interpolation is used to fill in the missing date between the 5-yearly observations. Source: Barro and Lee (1996, updated 2010).

Financial Development, 1984-2011: Domestic credit to the private sector (% of GDP), data are taken from Beck et al. (2012).

Trade, 1984-2011 : Sum of exports and imports (% of GDP), data are taken from WDI, World Bank (2013).

Distantness : Population weighted distance from the capital city of a country to capital cities of other countries, data are taken from CEPII (2013).

Inflation, 1984-2011 : Consumer prices (annual %), data are taken from WDI, World Bank

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