ESSAYS IN INTERNATIONAL MACROECONOMICS

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Abstract: This dissertation consists of two essays in international macroeconomics. Recent studies have found that once a country achieves a certain minimum level of financial development threshold, foreign direct investment (FDI) has a positive effect on economic growth. In the first essay, using both linear and nonlinear specifications, I examine whether this positive effect differs in systematic ways depending on the level of financial development of a country. The empirical analysis is based on a panel of 62 middle and high income countries spanning the period 1987-2016. The findings from this paper suggest that at low levels of financial development, improving domestic financial market conditions have the effect of enabling host economies maximized the growth benefit of FDI. However, the growth effect of FDI tends to become negligible as a country becomes more financially developed, suggesting that more finance is not always better.

The second essay explores the FDI-finance-growth relationship within and across convergence clubs. For this purpose, I first use the log t regression test for convergence and clustering proposed by Phillips and Sul (2007) to examine whether countries converge to a single long run equilibrium. I find evidence of convergence clustering among two different clubs based on financial development and four different clubs based on real per capita GDP. In the second part, I examine whether the growth effect of FDI differs across convergence clubs using the two-step system generalized method of moments (GMM) estimator with Windmeijer's (2005) finite sample correction. In addition, I test for threshold effect in the FDI-finance-growth relationship for each club using a dynamic panel threshold technique. The empirical analysis is based on a panel of 62 middle and high income countries spanning the period 1987-2016. Overall, the growth effect of FDI displays substantial heterogeneity across convergence clubs, appearing to be smaller in clubs with higher average financial development. The results also point to the presence of threshold effects. The positive effect of FDI on economic growth kicks in only after a country achieves a minimum level of financial development threshold. But there is also a financial development threshold beyond which the growth effect of FDI becomes negligible.

Keywords: Foreign direct investment, Financial development, Economic growth, System GMM, Dynamic panel threshold model, Club convergence

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CHAPTER I

IS MORE FINANCE BETTER? REEXAMINING THE FDI-FINANCE-GROWTH NEXUS

1. Introduction

Foreign direct investment (FDI) has become an integral part of the financial globalization process and a key catalyst to economic growth and development. Relative to other types of international capital flows, FDI is considered less volatile and less prone to reversals, suggesting that countries may be less vulnerable to reversals of these flows if capital inflows take the form of FDI. Policymakers, particularly in the developing, emerging, and transition economies have adopted effective strategies with a variety of preferential incentives aimed at attracting more FDI, especially following the debt crisis of the 1980s (Alfaro et al., 2004; Bluedorn et al., 2013). Many host countries have lowered various entry barriers, opened up new sectors to foreign investments, and provided various forms of investment incentives such as import duty exemptions and low taxes for foreign investors to encourage foreign owned companies to invest in their jurisdiction. It is therefore not surprising that the share of FDI in total capital flows has substantially increased over the past decades (Aitken and Harrison, 1999; Boubakri et al., 2013).

The strive to attract more FDI inflows stems from the belief that FDI inflows can bring not only the much-needed additional foreign capital but also new technology and know-how, new and improved managerial and marketing skills, and horizontal and vertical knowledge spillovers via backward or forward linkage with local firms. A commonly held belief among policymakers is that multinational corporations possess intangible productive assets in that they tend to be relatively more productive, skill and knowledge intensive, and invest in research and development. As a result, domestic firms will benefit from FDI through transfer from these multinational firms, that is, the process of technological diffusion (Hermes and Lensink, 2003; Javorcik, 2004; Kose et al., 2009; Alfaro, 2017; Desbordes and Wei, 2017). All these potential benefits of FDI inflows can potentially increase productivity and output, and transform the production structure of the host economy. However, these potential benefits are not automatic and may also vary across countries. Consequently, understanding the effects of FDI on the host economy is of considerable interest to policymakers and has become an important topic in academic and policy research.

A plethora of empirical studies have focused on the effects of FDI on economic growth in host economies. However, despite the theoretical reasons for expecting FDI to have a positive effect on economic growth, the empirical evidence at both micro and macro levels remains ambiguous. At the micro level, spillovers from FDI may affect the productivity of domestic firms through the horizontal (intra-industry) or vertical (inter-industry) spillover channels either via the backward or forward linkages between local and foreign firms.[1] Empirical micro studies find both positive and negative productivity spillovers that are more vertical rather than horizontal in nature. For example, Javorcik (2004) and Blalock and Gertler (2008) find evidence of positive productivity spillovers from foreign firms to their local upstream suppliers in Lithuania and Indonesia, respectively. Xu and Sheng (2012) observe, through forward linkages, FDI has a positive effect on Chinese manufacturing downstream firms. Using firm-level data from Romania, Javorcik and Spatareanu (2008) find only projects

with joint domestic and foreign ownership benefits from vertical spillovers. Other firm- and industry-level studies such as Aitken and Harrison (1999) on Venezuelan plants and Kathuria (2000) on Indian manufacturing industry find evidence of negative spillover effects.

Empirical studies at the macro level have also found mixed evidence albeit Lipsey (2002) observes that, where a significant relation exist, the overall evidence favors positive rather than negative effect. This reflects Bruno and Campos's (2013) observation from a review of 72 macro studies on FDI that 50 percent of the studies find positive growth effect, 11 percent find negative effect while 39 percent find no relationship between FDI and growth. The consensus in the empirical macro literature is that the positive growth effect of FDI is conditional on host country policies and environments, including financial sector development (Hermes and Lensink, 2003; Alfaro et al., 2004, 2010; Azman-Saini et al., 2010), human capital (Borensztein et al., 1998; Ford et al., 2008), trade openness (Balasubramanyam et al., 1996; Nair-Reichert and Weinhold, 2001), and level of economic development (Blomstrom et al., 1992). This suggests that FDI and host country characteristics are complementary in the technological spillover process.

A growing body of literature on the FDI-growth nexus has shown that a developed and a well-functioning financial sector is an important precondition for a positive growth effects of FDI (see, for example, Hermes and Lensink, 2003; Alfaro et al., 2004; Azman-Saini et al., 2010). Spillovers from FDI to local firms are not automatic or costless. The absence of a well-developed local financial sector can limit a host country's ability to benefit from potential spillovers from FDI. Entrepreneurial development and the adoption of best technological practices associated with FDI crucially depend on the development of the financial sector of the host country. By reducing the costs of conducting transaction, a well-developed financial sector ensures capital is allocated to the projects with the highest return, enhancing economic growth. Empirical evidence from existing studies implicitly suggest that once a host country achieves the minimum financial development threshold, the positive relation between FDI

and economic growth monotonically increases with financial development. However, recent studies on the growth-finance relationship have found that financial development promote economic growth up to some threshold beyond which the effect of more finance vanishes, becomes negligible, or turns negative (see, for example, Rioja and Valev, 2004a,b; Shen and Lee, 2006; Rousseau and Wachtel, 2011; Beck et al., 2014; Herwartz and Walle, 2014; Law and Singh, 2014; Arcand et al., 2015). If a well-functioning financial sector is an important precondition for a positive growth effect of FDI, then it is also possible that the effect of FDI on economic growth may vary with the level of financial development of the host country.

Given the relative importance of the financial sector in the FDI-growth nexus, this paper focuses on the complementarities between FDI and the host country's level of financial development. I ask two distinct but related questions. First, is the positive relationship between FDI and economic growth monotonically increasing with the level of financial development? Second, is there a financial development threshold beyond which the growth benefit of FDI becomes negligible, less pronounced or negative? Answers to these questions can provide insights into how changes in financial conditions in host economies will affect the growth benefit of FDI. It will also inform policy responses toward attracting more FDI. In the first part of the empirical investigation, I use a linear dynamic growth model to examine whether the positive relationship between FDI and economic growth monotonically increases with the level of financial development. Estimates are obtained using the two-step system generalized method of moments (GMM) estimator with Windmeijer's (2005) finite sample correction. In the second part, I test for the existence of a threshold effect in the FDI-finance-growth relationship using a dynamic panel threshold technique. The empirical analysis is based on a panel of 62 middle and high income countries spanning the period 1987-2016. Overall, consistent with the "vanishing effect" of financial development, I find significant and robust evidence of a positive growth effect of FDI; however, the effect tends to decline as a country becomes more financially developed. There is a financial development

threshold beyond which the positive effect of FDI on economic growth becomes negligible, suggesting that more finance is not always better. Using private credit as a measure of financial development, the results show that the effect of FDI on economic growth becomes statistically insignificant when private sector credit to GDP reaches 92.58%.

This paper contributes to the literature on the growth implication of FDI inflows in at least three major dimensions. The central contribution of this paper is the use of the dynamic panel threshold method by Kremer et al. (2013) to explore the nonlinear relationship between FDI, financial development, and economic growth. To the best of my knowledge, this method which extends the original model by Hansen (1999) and Caner and Hansen (2004) to allow for endogenous regressors in a panel setup has not been used to examine the FDI-finance-growth nexus. Second, unlike studies that test for the minimum threshold, this paper explores the "too much" finance hypothesis and thus tests for the existence of an upper financial development threshold effects in the FDI-finance-growth nexus. Finally, this paper complements the growing literature on structural and policy related conditions that can affect the relationship between FDI inflows and economic growth. In particular, this paper adds to this broader literature by showing that as countries increasingly implement financial sector reforms in part to stimulate FDI inflows, policymakers can expect the effect of FDI on economic growth to decline as a country becomes more financially developed. Thus, in the face of rapid financial sector reforms, it is important for policymakers to know how local financial development policies affect economic growth.

The rest of the paper is organized as follows. Section II provides a description of the data and preliminary evidence; section III describes the methodology. Section IV presents the empirical results, and section V concludes.

2. Data and preliminary analysis

The empirical analysis is based on a panel of 62 middle and high income countries over the period 1987-2016. This study focuses on the inflows of FDI to the host economy, therefore, I use net FDI inflow as a percentage of GDP as a measure of FDI. Net FDI inflows measure the net inflows of investment to acquire a lasting interest (10 percent or more of voting power) in an enterprise operating in an economy outside of the investor's. It is the sum of short-term and equity capital, reinvestment of earnings, and other long-term capital. Bank-based financial development measures are used as the measure of financial development.[2] In the finance-growth literature, private credit is the preferred measure of financial development (see, for example, Levine et al., 2000; Rioja and Valev, 2004a,b; Aghion et al., 2005, 2009). Thus, domestic credit to private sector as a percentage to GDP (hereafter private credit) is used as the primary measure of financial development. To provide a more nuanced view of the FDI-finance-growth relationship, I use three other measures: domestic credit to private sector by banks as a percentage of GDP (hereafter bank credit), liquid liabilities as a percentage of GDP, and a new broad-based index of financial development developed by the IMF namely, financial institution index (Sahay et al., 2015).[3] Private credit and bank credit are obtained from the World Banks World Development Indicators database. The growth of real GDP per capita in constant 2010 dollars is used as a measure of growth rate of output.

The control variables are the initial level of real GDP per capita to control for the convergence effect in the standard growth theory; average years of education completed among people over age 25 to control for the level of human capital in the country; the government size (government consumption/GDP), the CPI-based average inflation rate, and openness to trade ((exports+import)/GDP) as controls for policy in the country. Large government size and high inflation rate are presumed to negatively affect growth, while trade openness affects growth positively. Domestic investment is also included for further robustness check.

All the control variables, FDI inflows and domestic investment are extracted from the World Banks World Development Indicators. The average years of schooling data are obtained from Barro and Lee (2013) Educational Attainment Data.

As is now standard in the cross-country growth literature, to filter out cyclical fluctuations and to focus on long-run growth, the data are averaged over 3-year non-overlapping periods[4] so there are ten observations per country. Table 1 presents the descriptive statistics for all the variables. In the preliminary discussion, I focus on the main variables of interest: private credit, FDI, and growth. As shown in Table 1, there is substantial variation in private credit across countries, ranging from 2.3 percent in Sudan to 268.3 percent in Iceland; economic growth ranges from -7.4 percent in Cameroon to 10.8 percent in Botswana. FDI as a share of GDP also ranges extensively, from -5.8 percent in Panama to 56.7 percent in Netherlands.

To provide context for the analysis, countries are ranked according to their average level of financial development measured by private credit over the sample period, and then split into bottom half and top half subsamples.[5] Figure 1 plots the average FDI as a share of GDP over the sample period against the average private credit over the sample period for the full, bottom half, and top half samples. As shown in Figure 1, there is clearly a positive relationship between the two variables in both the full sample and the bottom half subsample. However, there appears to be no relationship between average FDI and average private credit in the top half subsample. Table 2 also shows the cross-country correlation among the main variables for the full, top half, and bottom half samples. Overall, there is a positive correlation between FDI and private credit. However, the correlation appears stronger and statistically significant at the 5 percent level in the bottom half subsample but relatively weaker in the top half subsample.

The results in Figure 1 and Table 2 represent preliminary evidence that the relationship between FDI and financial development vary with the level of financial development. If financial development plays a role in mediating the potential growth benefit of FDI, then

one can expect countries with the same levels of FDI to experience different growth effect; the growth effect of FDI will vary with the level of financial development. The goal of this paper is to examine the robustness of these findings.

3. Econometric methodology

The empirical investigations are of two parts. In the first part, I use a linear dynamic growth model to examine whether the positive relationship between FDI and economic growth monotonically increases or decreases with the level of financial development. The second part involves the use of dynamic panel threshold model to test for the existence of a threshold effect in the FDI-finance-growth relationship.

3.1. Linear dynamic model

In this section, I use split-sample regressions to test for potential differences in coefficients across subsamples and an interaction analysis to examine how the growth effect of FDI varies with the level of financial development of a country.

3.1.1. Split-sample regressions

As a starting exercise, I split the sample into bottom half and top half subsamples according to their average level of financial development, and then estimate split-sample regressions to test for potential coefficient changes across subsamples. Within each group of countries, I estimate the following cross-country growth equation:

$$y_{i,t} - y_{i,t-1} = (\alpha - 1)y_{i,t-1} + \beta' X_{i,t} + \mu_i + \varepsilon_{i,t}. \tag{1}$$

where $y_{i,t}$ is the logarithm of real per capita GDP in country i at time t, and $X_{i,t}$ is a set of explanatory variables, including FDI, average years of schooling, government consumption expenditure, inflation rate, and trade openness, μ_i represents time invariant country-specific effect, and $\varepsilon_{i,t}$ denotes the idiosyncratic shocks.[6] All variables, with the exception of inflation, are transformed into logarithms. "Too much" finance implies that the estimated coefficient for FDI will be less positive in the top half subsample. To obtain asymptotically efficient estimates of the effect of FDI on growth, I use the system dynamic panel GMM estimator by Arellano and Bover (1995) and Blundell and Bond (1998).[7] This dynamic panel estimator has a number of advantages over pure cross-sectional estimators. First, the system dynamic panel GMM estimator addresses the potential endogeneity of all explanatory variables. Second, it accounts for the biases induced by including lagged or initial income in the growth equation. Third, unlike pure cross-sectional instrumental variable estimators, the system GMM estimator exploits the time series variation and controls for unobserved country-specific effect.

Rewrite Equation (1) as

$$y_{i,t} = \alpha y_{i,t-1} + \beta' X_{i,t} + \mu_i + \varepsilon_{i,t}. \tag{2}$$

To eliminate the unobserved country-specific effects, Holtz-Eakin et al. (1988) and Arellano and Bond (1991) suggest to first-difference Equation (2) as follows:

$$y_{i,t} - y_{i,t-1} = \alpha(y_{i,t-1} - y_{i,t-2}) + \beta'(X_{i,t} - X_{i,t-1}) + (\varepsilon_{i,t} - \varepsilon_{i,t-1}). \tag{3}$$

By construction, in Equation (3), the differenced lagged dependent variable $(y_{i,t-1} - y_{i,t-2})$ is correlated with the new error term $(\varepsilon_{i,t} - \varepsilon_{i,t-1})$. The former contains $y_{i,t-1}$ and the latter, now an MA(1) process, contains $\varepsilon_{i,t-1}$. To address this correlation and the potential

endogeneity of the explanatory variables, Arellano and Bond (1991) suggest using the lagged levels of the explanatory variables as instruments under the assumptions that the error term, ε, is not serially correlated and the explanatory variables are weakly exogenous.[8] Under these assumptions, this dynamic panel estimator, commonly referred to as *difference* GMM estimator, uses the following moment conditions:

$$E[y_{i,t-l}(\varepsilon_{i,t} - \varepsilon_{i,t-1})] = 0 \text{ for } l \geq 2;\ t = 3, \ldots, T. \tag{4}$$

$$E[X_{i,t-l}(\varepsilon_{i,t} - \varepsilon_{i,t-1})] = 0 \text{ for } l \geq 2;\ t = 3, \ldots, T. \tag{5}$$

The *difference* GMM estimator, however, has conceptual and statistical shortcomings. For example, Blundell and Bond (1998) and Alonso-Borrego and Arellano (1999) demonstrated that persistence in the lagged dependent and explanatory variables makes lagged levels of these variables weak instruments for the differenced variables and this may adversely affect the small-sample and asymptotic properties of the *difference* GMM estimator. To address this weak instrument problem and to improve efficiency, Arellano and Bover (1995) and Blundell and Bond (1998) proposed the *system* GMM estimator. The *system* GMM estimator augments the *difference* estimator by jointly estimating the regressions in differences and levels. The two equations are distinctly instrumented. While the instruments for the regression in differences are the lagged levels of the explanatory variables (same as above), the instruments for the equation in levels are the lagged differences of the explanatory variables.

These instruments are valid under the additional assumption that the correlation between the country-specific effect, μ_i, and the levels of the explanatory variables is time-invariant such that

$$E[y_{i,t+p}\mu_i] = E[y_{i,t+q}\mu_i] \text{ and } E[X_{i,t+p}\mu_i] = E[X_{i,t+q}\mu_i] \text{ for all } p \text{ and } q. \tag{6}$$

Given this assumption, there is no correlation between the country-specific effect, μ_i, and the differences of the explanatory variables. This assumption implies, for example, that any correlation between FDI or financial development and the country-specific effect is constant over time. Thus, the lagged differences of the explanatory variables are valid instruments for the equation in levels, and the additional moment conditions for the regression in levels are:

$$E[(y_{i,t-l} - y_{i,t-l-1})(\mu_i + \varepsilon_{i,t})] = 0 \text{ for } l = 1, \tag{7}$$

$$E[(X_{i,t-l} - X_{i,t-l-1})(\mu_i + \varepsilon_{i,t})] = 0 \text{ for } l = 1. \tag{8}$$

The *system* GMM thus consists of regressions in differences and levels stacked together. The *system* GMM estimator uses the moment conditions in Equations (4), (5), (7) and (8) to obtain consistent and efficient estimates. The moment conditions in Equations (4) and (5) are used in the first part of the system (regressions in differences) while the moment conditions in Equations (7) and (8) are used in the second part of the system (regressions in levels). As with other GMM estimators, the *system* GMM have one- and two-step variants. Although asymptotically more efficient and robust to heteroscedasticity, the two-step *system* GMM estimation of the standard errors tend to be severely downward biased in finite samples. To eliminate this potential bias, I use the finite sample correction for the two-step covariance matrix derived by Windmeijer (2005).[9]

The consistency of the *system* GMM estimator relies on the validity of the instruments and the assumption that the error term, ε, is not serially correlated. Although, by construction, the residuals in first differences, AR(1), are likely to be serially correlated, there should be no second-order, AR(2), serial correlation. I use two specification tests proposed by Arellano and Bond (1991) and Blundell and Bond (1998) to test these two assumptions. Hansen test of over-identifying restrictions is used to test the overall validity of the instruments.[10] The second test examines the hypothesis that the differenced error term is not second-order

serially correlated.[11][12] Also, Roodman (2009) observed that instrument proliferation can result in biased parameter estimates. To reduce this instrument count problem, I "collapse" the instrument matrix in order to keep the number of instruments far below the number of countries.[13] In summary, I estimate the cross-country growth model using the two-step *system* GMM estimator with Windmeijer's (2005) finite sample correction for the covariance matrix.

3.1.2. Interaction analysis

As an alternative to the split-sample regressions, I form a linear interaction term between FDI and financial development and use it as a regressor to test whether the coefficient of FDI depends on the level of financial development of a country. Separate FDI from the set of explanatory variables and rewrite Equation (1) as follows:

$$y_{i,t} - y_{i,t-1} = (\alpha - 1)y_{i,t-1} + \delta FDI_{i,t} + \beta' X_{i,t} + \mu_i + \varepsilon_{i,t}. \tag{9}$$

Let the coefficient of FDI, δ, depends on the level of financial development of a country so that

$$\delta = \gamma_1 + \gamma_2 FD_{i,t} \tag{10}$$

where $FD_{i,t}$ is a measure of financial development. Substitute Equation (10) into Equation (9) to get

$$y_{i,t} - y_{i,t-1} = (\alpha - 1)y_{i,t-1} + \gamma_1 FDI_{i,t} + \gamma_2 FDI_{i,t} * FD_{i,t} + \beta' X_{i,t} + \mu_i + \varepsilon_{i,t}. \tag{11}$$

Equation (11) is a standard growth regression augmented with the interaction term, $FDI_{i,t} * FD_{i,t}$. The hypothesis is that $\gamma_1 > 0$ and $\gamma_2 < 0$ so that the growth effect of FDI, $\gamma_1 + \gamma_2 * FD_{i,t}$, is lower at high levels of financial development. Equation (11) is also estimated using

the two-step *system* GMM estimator with Windmeijer's (2005) finite sample correction for the covariance matrix.

3.2. Dynamic panel threshold model

In the split-sample regressions, the sample is divided in a rather ad hoc fashion. However, because the appropriate threshold level is not known a priori, results from split-sample regressions may be sensitive to the cut-off value. On the other hand, the linear interaction model places a priori restriction that the growth effect of FDI monotonically increases or decreases with financial development. For these reasons, I use the dynamic panel threshold method by Kremer et al. (2013) to test for the existence of a threshold effect in the FDI-growth relationship.[14] This method extends the original model by Hansen (1999) and Caner and Hansen (2004) to allow for endogenous regressors in a panel framework.

If financial development plays a role in mediating the growth effect of FDI, regression functions will not be identical across all countries. With no prior knowledge of the cut-off values, rather than arbitrarily assuming cut-off values, appropriate threshold level of financial development is estimated using the dynamic panel threshold method. The dynamic panel threshold model of the FDI-finance-growth nexus takes the following form:

$$\begin{aligned} Growth = \mu_i + \beta_1 FDI_{i,t} I(FIN_{i,t} \leq \gamma) + \delta I(FIN_{i,t} \leq \gamma) \\ + \beta_2 FDI_{i,t} I(FIN_{i,t} > \gamma) + \psi' X_{i,t} + \varepsilon_{i,t} \end{aligned} \tag{12}$$

where $Growth$ is the growth rate of real per capita GDP in country i at time t, μ_i is the country-specific fixed effect, γ is the threshold level, and the error term is $\varepsilon_{i,t} \overset{i.i.d}{\sim} (0, \sigma^2)$. $I(\cdot)$ is an indicator function taking a value of 1 if the argument in the indicator function holds, and 0 otherwise. The threshold variable, $FIN_{i,t}$, divides the sample into regimes with differing regression slope parameters β_1 and β_2. The level of financial development

measured by either private credit, bank credit, liquid liabilities, or financial institution index is used as the threshold variable. $X_{i,t}$ is a vector of explanatory variables which can be partitioned into a subset of exogenous variables ($X_{1i,t} = schooling$, $government\ expenditure$, $inflation\ rate$, $trade\ openness$) uncorrelated with $\varepsilon_{i,t}$, and a subset of endogenous variable ($X_{2i,t} = real\ per\ capita\ GDP\ from\ previous\ period$) correlated with $\varepsilon_{i,t}$. Allowing for differences in the regime intercept helps minimize any potential bias in both the threshold and the corresponding marginal effect estimates. Following Bick (2010), I include a threshold intercept, δ.[15] All variables, with the exception of inflation and growth, are transformed into logarithms.

Since the threshold level, γ, is not known a priori, it must be estimated. The estimation procedure involves eliminating the country-specific fixed effects μ_i using a fixed-effect transformation method. In a dynamic panel threshold model, however, the traditional within-transformation and first differencing methods of removing individual effects leads to inconsistent estimates as it violates the distributional assumptions underlying the threshold model by Hansen (1999). Thus, the forward orthogonal deviations transformation method by Arellano and Bover (1995) is used to eliminate the country-specific fixed effects.[16] The estimation procedure by Caner and Hansen (2004) can now be applied to Equation (12).[17]

Following Caner and Hansen (2004), the parameters are estimated sequentially. First, I run a reduced-form regression of the endogenous variable $X_{2,it}$ on a set of instruments $Z_{1,it}$, including all exogenous regressors $X_{1i,t}$. I then obtain the predicted values $\hat{X}_{2,it}$. Second, in Equation (12), I replace $X_{2,it}$ with $\hat{X}_{2,it}$ and then obtain the least square estimates for a fixed threshold γ. Let $S(\gamma)$ denote the resulting sum of squared residuals. For a strict subset of the support of $FIN_{i,t}$, I repeat this second step. Observe that, since the slope parameters depend on the threshold value, the sum of squared errors (SSE) for Equation (12) which is also a function of the threshold value is a step function, with the steps occurring at some well-defined values of the threshold variable $FIN_{i,t}$. Conditioning on a threshold value,

however, SSE is linear in the parameters and minimization will yield the conditional OLS estimates for β_1 and β_2. Finally, the estimator of the threshold corresponds to the value of γ that produces the smallest sum of squared residuals. That is, the minimizer of the sum of squared residuals: $\hat{\gamma} = \underset{\gamma}{\operatorname{argmin}}\, S_n(\gamma)$.[18]

Let $C(\alpha)$ be the 95% percentile of the asymptotic distribution of the likelihood ratio statistic $LR(\gamma)$, then the critical values for determining the 95 percent confidence interval of the threshold value are given by $\Gamma = \{\gamma : LR(\gamma) \leq C(\alpha)\}$ (Hansen, 1999; Caner and Hansen, 2004). Once the sample-splitting threshold estimate $\hat{\gamma}$ is obtained, the sample can be divided into subsamples and, on each subsample, the slope parameters β_1 and β_2 can be estimated by generalized method of moments (GMM). Lags of the dependent variable are used as instruments. Given the bias-efficiency tradeoff in finite sample, empirical results based on GMM may depend on the number of instruments (Windmeijer, 2005; Roodman, 2009). Therefore, in estimation, I use different lag lengths. To avoid potential overfitting, I use a lag length of one, and to increase efficiency, I use all available lags as instruments. However, the choice of instruments did not have any significant effect on the main results. In the results reported in this paper, I use an instrument count of two.

4. Empirical results

The results from the linear and dynamic panel threshold models are discussed in turn.

4.1. Linear dynamic model

In a pure cross-sectional analysis, Alfaro et al. (2004) find no significant direct effect of FDI on growth. Their sample consisted of only 28 percent developed countries so it is more likely that most of the countries in their sample have not achieved the minimum level of

financial development threshold. The authors conjectured that the result could be driven by the composition of the sample. When they interact FDI with financial development measures, the interaction term turns out to be positive and significant. Similarly, Rioja and Valev (2004a) observe finance has positive effect on growth when private credit to GDP is greater than 14 percent. These findings suggest that FDI can have direct effect on growth in countries where the financial markets are well-developed.

In this paper, the sample consist of only middle and high income countries. Over the sample period, 58 out of 62 countries (94%) have an average level of private credit to GDP exceeding 14 percent so I would expect FDI to have a direct effect on growth. To test this proposition and to have reference for comparison to estimates using subsamples, for both the full sample and subsamples, I estimate Equation (1) using the two-step *system* GMM estimator with Windmeijer's (2005) finite sample correction. Table 3 presents these results using 3-year averages.[19]

As shown in column (1) of Table 3, the estimated coefficient of FDI is positive and statistically significant at the 1 percent level, suggesting that FDI has direct positive effect on growth. Columns (2) and (3) show the results for the top half and bottom half subsamples, respectively. The estimated coefficients of FDI for both subsamples are significantly positive. However, the coefficient of FDI is substantially lower in the top half subsample than in the bottom half. Also, relative to the full sample, the growth effect of FDI in the bottom half sample is larger in magnitude but smaller in the top half. Columns (4),(5), and (6) show the results using three groups: the top, middle, and bottom third subsamples. Similar to the results from the two-way split, the estimated coefficient of FDI decreases as we move up from the bottom third to the top third. In the top third, the coefficient of FDI is not significantly different from zero. The FDI coefficient for the bottom third (0.321), however, is significantly positive and larger in magnitude than that in the middle third (0.231).

If the growth effect of FDI tends to decline with higher levels of financial development,

one would expect to observe similar pattern between middle and high income countries, with the estimated effect being larger in the middle income subsample of countries.[20] Columns (1) and (2) of Table 4 show the results of the differential effect in middle and high income countries. Consistent with the previous results, the estimated coefficient is larger in middle income countries than it is in high income countries. Overall, the split-sample regressions provide evidence of potential nonlinearity in the FDI-finance-growth relationship.

Turning to the interaction analysis, the last three columns of Table 4 present the estimation results from Equation (11). As shown in column (3), the interaction between FDI and private credit turns out to be negative and statistically significant at the 5 percent level, leading to the conclusion that the growth effect of FDI declines with increased financial development. To see how the results are robust to different measures of financial development, columns (4) and (5) of Table 4 show the results using bank credit and liquid liabilities as a financial development measures, respectively. The results are identical to the case where private credit is used as a measure of financial development; the interaction term turns out to be negative and significant. Thus, more finance is not always better. Moreover, the results provide additional evidence supporting potential financial development threshold effect given that, in columns (3), (4), and (5), the coefficient of FDI and the interaction term have opposite signs. As indicated by the F-statistic for FDI, the coefficient of FDI and the interaction term are jointly significant at the 5 percent level in all cases.

As shown in Tables 3 and 4, in all subsamples and specifications, the estimated coefficient of initial income is negative. This is consistent with β-convergence. All the other explanatory variables have the expected sign whenever significant. Also, the Arellano-Bond serial correlation test shows that there is no second-order serial correlation while the Hansen instrument validity test shows that the instruments are not correlated with the error term.

In summary, the results based on the split-sample regressions and the interaction analysis bear out the possibility of nonlinearity in the FDI-finance-growth relationship. The

interaction between FDI and financial development displays nonlinearity. The implication is that the more financially developed a country is, the effect of FDI on growth appears to be smaller. These findings are consistent with the declining growth effect of financial development reported in the literature (see, for example, Rioja and Valev, 2004a,b; Aghion et al., 2005; Shen and Lee, 2006; Rousseau and Wachtel, 2011; Arcand et al., 2015).

4.2. Dynamic panel threshold model

Although the split-sample regressions and the interaction analysis appear informative, each has shortcomings. For example, the linear interaction model places a priori restriction that the growth effect of FDI monotonically increases or decreases with financial development. In the split-sample regressions, the sample is divided in a rather ad hoc fashion and hence standard asymptotic confidence intervals as well as the chi-square approximation may be inaccurate (Hansen, 2000). For these reasons, I test for the existence of a threshold effect in the FDI-growth relationship using a dynamic panel threshold model. Table 5 presents the estimates from the dynamic panel threshold model (Equation (12)).

Column (1) of Table 5 shows the benchmark results where the financial development measure, private credit, is used as the threshold variable. The first row displays the estimated financial development threshold values and the corresponding 95 percent confidence intervals. The slope parameters estimates, $\hat{\beta}_1$ and $\hat{\beta}_2$, denote the regime-dependent marginal effects of FDI on growth. The point estimate of the threshold value is 92.58% of GDP.[21] Approximately 25 percent of the observations in the sample are above this threshold value; 17 countries have average private credit over the sample period exceeding the threshold value of 92.58 percent. The 95 percent confidence interval for the threshold is [83.75, 97.49]. The literature on the FDI-finance-growth relationship has not considered the upper financial development threshold effect, thus limiting comparisons. However, the threshold value of 92.58

percent is close to the threshold estimates in the finance-growth literature (see, for example, Arcand et al., 2015; Law and Singh, 2014). With respect to the regime-dependent marginal effects, FDI has significantly positive effect on economic growth if private credit is less than the threshold value. Above the threshold, however, the effect of FDI is not statistically significant. Initial income, schooling, and all the "policy" covariates are either significant and plausibly signed or insignificant.

To provide a more nuanced view, the last three columns of Table 5 present estimates using bank credit, liquid liabilities, and financial institution index as alternative measures of financial development, respectively. The results are qualitatively similar. Unlike the other three measures, when liquid liabilities is used as the measure of financial development, the effect of FDI is statistically significant both above and below the threshold value. However, consistent with the diminishing returns effect of financial development, the effect is relatively smaller when liquid liabilities exceeds the threshold level. To examine the sensitivity of the benchmark results, following Levine et al. (2000) and Beck et al. (2000), I re-estimate the model using a "simple" conditioning set that includes only the logarithm of initial income and educational attainment. The results are reported in Table 6. The results remain robust. In particular, the point estimate of the threshold value and the marginal effects are similar to the benchmark results. In summary, the empirical findings are robust to alternative conditioning sets and measures of financial development.

The picture that emerges from the empirical findings is that there is a financial development threshold effect in the FDI-finance-growth relationship; the growth effect of FDI tends to decline as a country becomes more financially developed. These findings are robust to alternative conditioning sets, estimation procedures, and measures of financial development. They are also consistent with the "vanishing effect" of financial development (see, for example, Rioja and Valev, 2004a,b; Shen and Lee, 2006; Rousseau and Wachtel, 2011; Beck et al., 2014; Herwartz and Walle, 2014; Law and Singh, 2014; Arcand et al., 2015); there is

a threshold beyond which the positive effect of FDI on economic growth becomes negligible, suggesting that more finance is not always better.

5. Conclusion

Empirical studies on FDI and economic growth relationship have found that once a country achieves a certain minimum level of financial development threshold, FDI has a positive effect on economic growth. In this paper, I examine whether this positive effect differs in systematic ways depending on the level of financial development of a country. I ask two distinct but related questions. First, is the positive relationship between FDI and economic growth monotonically increasing with the level of financial development? Second, is there a financial development threshold beyond which the growth benefit of FDI becomes negligible, less pronounced or negative? The empirical analysis is based on a panel of 62 middle and high income countries spanning the period 1987-2016.

In the first part of the empirical investigation, I use linear dynamic growth model to examine whether the positive relationship between FDI and economic growth monotonically increases or decreases with the level of financial development. I use split-sample regressions to test for potential differences in coefficients across subsamples and an interaction analysis to examine how the growth effect of FDI varies with the level of financial development of a country. Estimates are obtained using two-step system generalized method of moments (GMM) estimator with Windmeijer's (2005) finite sample correction. The second part involves the use of a dynamic panel threshold model to test for the existence of threshold effect in the FDI-finance-growth relationship. A central contribution of this paper is the adoption of the dynamic panel threshold method by Kremer et al. (2013) to explore the nonlinear relationship between FDI, financial development, and growth. The dynamic panel thresh-

old model allows endogenous test for the existence of threshold effect in the FDI-growth relationship without imposing any specific functional form or arbitrary data splitting.

I find significant and robust evidence of a positive growth effect of FDI, however, the effect tends to decline as a country becomes more financially developed, suggesting a threshold effect in the FDI-finance-growth relationship. Using private credit as a measure of financial development, the results show that the effect of FDI on economic growth becomes statistically insignificant when private sector credit to GDP reaches 92.58 percent. This paper adds to the broader literature on structural and policy related conditions that can affect the relationship between FDI inflows and economic growth by showing that as countries increasingly implement financial sector reforms in part to stimulate FDI inflows, policymakers can expect the effect of FDI on economic growth to become negligible as a country becomes more financially developed.

Overall, the findings from this paper suggest that at low levels of financial development, improving domestic financial market conditions have the effect of enabling host economies maximized the growth benefit of FDI. However, the growth effect of FDI tends to become negligible as a country becomes more financially developed, suggesting that more finance is not always better. Thus, in the face of rapid financial market reform, it is imperative for policymakers especially, in developing, emerging, and transition economies, to know how financial development policies affect economic growth. Also, to accurately examine the role of financial development in mediating the potential growth benefit of FDI, it is important for researchers to allow for cross-country differences in financial development.

CHAPTER II

HETEROGENEITY AND NONLINEARITY IN THE FDI-FINANCE-GROWTH NEXUS: EVIDENCE FROM CONVERGENCE CLUBS

1. Introduction

The role of financial development in the foreign direct investment (FDI)-growth nexus has become an important topic in academic and policy research. Starting from the seminal contribution of Alfaro et al. (2004), a large body of empirical studies has focused on the growth benefit of FDI in the host economy and the role of local financial development in mediating this potential benefit (see, for example, Hermes and Lensink, 2003; Alfaro et al., 2010; Azman-Saini et al., 2010; Alfaro, 2017). Findings from these studies show countries with well-developed financial sector gain significantly from FDI inflows. In addition, local financial sector development affects the locational decisions of multinational corporations. For example, it has been observed that, through the financing effect, host countries with well-functioning financial sector attract more multinational affiliates. The level of financial development in a host country can also affect the scale of operation of multinational firms.[22]

However, when local financial institutions are underdeveloped, host-country financing is often insufficient, costly, and of shorter duration, serving as a deterrent to multinational corporations seeking to establish a local affiliate (Bilir et al., 2014).

Many host countries have undergone financial sector reforms such as relaxing restrictions on foreign bank entry and cross-border bank alliances in part to attract more FDI inflows. They have increasingly offered investment incentives to encourage foreign firms invest in their jurisdiction (Alfaro et al., 2004; Bluedorn et al., 2013; Alfaro, 2017). A commonly held belief among policymakers, particularly in the developing, emerging, and transition economies is that FDI generates positive effects for host countries. In addition to the direct capital financing it supplies, FDI inflows can bring new technology and know-how, new and improved managerial and marketing skills while promoting backward and forward linkages with local firms. These potential benefits of FDI can play a significant role in promoting economic growth and development of a host country.

Given the panoply of potential benefits of FDI inflows, a plethora of empirical studies have focused on the effects of FDI on economic growth in host economies. Theoretical benefits notwithstanding, empirical studies on the growth effect of FDI at both micro and macro levels find mixed evidence.[23] Given the mixed empirical evidence, coupled with the many incentives offered to foreign firms, understanding the factors that affect the locational decisions of multinational firms and the conditions under which host economies benefit from FDI are of considerable interest to policymakers. The consensus in the empirical literature is that the growth benefit of FDI is not automatic but conditional. At the micro level, the growth benefit of FDI depends on the type of linkage (backward or forward)[24] while at the macro level, it depends on the host country policies and environments, including local financial sector development, trade openness, and the level of economic and human capital development. Given the appropriate host country policies and environments, a preponderance of studies have shown that FDI inflows can increase productivity, assist human capital formation,

create a more competitive business environment, and transform the production structure of the host economy(see, for example, Blomstrom et al., 1992; Nair-Reichert and Weinhold, 2001; Hermes and Lensink, 2003; Javorcik, 2004; Alfaro et al., 2004).

The goal of this paper is to shed light on the potential heterogeneity and nonlinearity in the FDI-finance-growth nexus. For this purpose, I first explore whether the relationship between FDI and economic growth is significantly positive and whether the effect differs across more homogenous group of countries. Second, within each homogenous group of countries, I ask whether there is a common financial development threshold beyond which the positive effect of FDI on economic growth changes in magnitude.

The empirical investigation is twofold. First, I apply the log t regression test for convergence and clustering proposed by Phillips and Sul (2007) to examine whether countries converge to a single long run equilibrium or whether there exist multiple equilibria (convergence clubs) in terms of real per capita GDP and financial development. Results based on the convergence test suggest that all the countries in the sample do not converge to a single long run equilibrium. However, there is some evidence of convergence clustering among two different clubs based on private credit, a measure of financial development, and four different clubs based on real per capita GDP.[25] In the second part, for each convergence club, I use a linear dynamic growth model to examine the relationship between FDI and economic growth. Estimates are obtained using the two-step system generalized method of moments (GMM) estimator with Windmeijer's (2005) finite sample correction. In addition, I test for threshold effect in the FDI-finance-growth relationship for each club using a dynamic panel threshold technique by Kremer et al. (2013). The empirical analysis is based on a panel of 62 middle and high income countries spanning the period 1987-2016.

Overall, the empirical results suggest the possibility of heterogeneity and nonlinearity in the FDI-finance-growth nexus. The growth effect of FDI displays substantial heterogeneity across convergence clubs, appearing to be smaller in clubs with higher average financial

development. The results also point to the presence of threshold effects. The positive effect of FDI on economic growth kicks in only after a country achieves a minimum level of financial development threshold. But there is also a threshold beyond which the growth effect of FDI becomes negligible. These results are consistent with the diminishing returns effects in the development of financial sector. While, in this paper, I test for possible structural breaks in terms of the level of financial development, I do not examine the channels through which the nonlinear relationship occurs.

This paper makes the following contributions to the empirical literature on growth implication of FDI inflows. First, to the best of my knowledge, this is the first paper to explore heterogeneity and nonlinearity in the FDI-finance-growth relationship within and across convergence clubs. Existing FDI-related studies focus on conventional classification of countries or sample splitting based on income levels, level of financial development, and geography to examine heterogeneity. Unlike these studies, however, the time varying nonlinear factor model-based convergence test and the algorithm used to cluster countries into convergence clubs in this paper allows for transitional dynamics and individual heterogeneity, thus avoiding ad hoc sample splitting. I find that club members are not necessarily geographically neighboring, and neither does income convergence necessarily imply financial development convergence. Second, by grouping countries into convergence clubs based on financial development, this paper tests for the existence of both lower and upper financial development threshold effects. Previous studies usually focus on the minimum threshold. Third, this paper is one of the first papers to use a dynamic panel threshold method to explore the nonlinear relationship between FDI, financial development and economic growth. Finally, this paper contributes to the growing literature on structural and policy related conditions that can affect the relationship between FDI inflows and economic growth by showing that heterogeneity and nonlinearity matter in the relationship.

The rest of the paper is organized as follows. Section II provides a description of the

data and preliminary evidence; section III describes the methodology. Section IV presents the empirical results, and section V concludes.

2. Data

The empirical analysis is based on a panel of 62 middle and high income countries over the period 1987-2016. I use net FDI inflow as a percentage of GDP as a measure of FDI since this paper focuses on the inflows of FDI to the host economy.[26] Net FDI inflow is the sum of short-term and equity capital, reinvestment of earnings, and other long-term capital. I use Bank-based financial development measures as the measure of financial development.[27] In the finance-growth literature, private credit as a percentage of GDP is the preferred measure of financial development (see, for example, Levine et al., 2000; Rioja and Valev, 2004a; Aghion et al., 2005, 2009). Thus, domestic credit to private sector as a percentage of GDP (hereafter private credit) is used as the primary measure of financial development. Private credit is obtained from the World Bank's World Development Indicators database. The growth of real GDP per capita in constant 2010 dollars is used as a measure of growth rate of output.

As control variables, following the literature, I include initial level of real GDP per capita to control for the convergence effect in the standard growth theory; average years of education completed among people age 25 and over to control for the level of human capital in the country; government size (government consumption/GDP), CPI-based average inflation rate, and openness to trade ((exports+import)/GDP) as controls for policy in the country. Large government size and high inflation rate are presumed to negatively affect growth, while trade openness affects growth positively. All the control variables and FDI inflows are extracted from the World Banks World Development Indicators. The average years of schooling data

are obtained from Barro and Lee (2013) series.

Following the literature, I use annual data for the log t regression test for convergence and clustering. However, to explore the FDI-finance-growth relationship within and across convergence clubs, the data are averaged over 3-year non-overlapping periods so there are ten observations per country.[28] This is standard in the cross-country growth literature and is done to filter out cyclical fluctuations and to focus on long-run growth.

3. Econometric methodology

The empirical investigations are of two parts. In the first part, I apply the log t regression test for convergence and clustering proposed by Phillips and Sul (2007) to examine whether countries converge to a single long run equilibrium or whether there exist multiple equilibria (convergence clubs) in terms of real per capita GDP and financial development. In the second part, I explore the FDI-finance-growth relationship within and across convergence clubs.

3.1. Convergence tests

In this section, I first review the conventional β-convergence test and the potential shortcomings associated with it. Next, I describe the log t regression test for convergence and clustering proposed by Phillips and Sul (2007) in the context of a time varying nonlinear factor model.

3.1.1. β-convergence test

As a preliminary exercise to the convergence analysis, I examine whether the speed of convergence parameter is positive or negative by regressing the average growth rate of $y = \{private$

credit, *real per capita GDP*} on its initial value. That is, I examine whether areas with low initial financial development measured by private credit or low initial real per capita GDP tend to experience faster growth rates in financial development and real per capita GDP, respectively. This is the conventional β-convergence test. A negative relationship between the average growth rate of $y = \{private\ credit, real\ per\ capita\ GDP\}$ and its initial level implies β-convergence.

The left panel of Figure 2 shows the relationship between initial log private credit and average growth rate of private credit for the full sample. If all countries are converging overtime, the scatter plot would show a strong negative association between initial log private credit and the average growth rate of private credit.[29] When the sample is divided into bottom half (circle-shaped) and top half (triangle-shaped) subsamples according to their average level of financial development, the negative association becomes relatively stronger, suggesting the possibility of a weak form of regional catch-up. Similarly, in the right panel of Figure 2, relative to the full sample, the negative relationship between initial log real per capita GDP and average growth rate of real per capita GDP appears more pronounced in the middle and high income subsamples.[30]

The results in Figure 2 represent preliminary evidence that countries in the sample may generally diverge in terms of private credit and real per capita GDP; countries in a subgroup that have similar characteristics tend to converge to their own steady state. The problem with using the conventional β-convergence test for club convergence is that the subgroups of countries have to be determined a priori. Moreover, the test works under homogeneity of technology progress. However, as observed by Phillips and Sul (2009), under conditions of transitional heterogeneity, estimation of the convergence parameter may be bias and inconsistent so negative estimates cannot be directly taken as evidence of growth convergence. In this paper, I use time varying nonlinear factor model that incorporates transitional dynamics and individual heterogeneity.

3.1.2. The log t test

Let $y_{i,t}$ be the log private credit or log real per capita GDP of country i at time t. To analyze the transitional dynamics of $y_{i,t}$, I apply a regression-based convergence test developed by Phillips and Sul (2007). This log t regression test is based on a nonlinear time-varying factor model. As a starting point of the model, the panel data $y_{i,t}$ is decomposed as

$$y_{i,t} = g_{i,t} + a_{i,t}, \tag{13}$$

where $g_{i,t}$ denotes the systematic components including permanent common components and $a_{i,t}$ represents transitory components. It is possible that the elements $g_{i,t}$ and $a_{i,t}$ may contain a combination of common and idiosyncratic components. In order to isolate common from idiosyncratic components in the panel, Equation (13) is transformed as

$$y_{i,t} = \left(\frac{g_{i,t} + a_{i,t}}{\mu_t}\right)\mu_t = \delta_{i,t}\mu_t \text{ for all } i \text{ and } t, \tag{14}$$

where μ_t is a single common component capturing some deterministic or stochastically trending behavior and $\delta_{i,t}$ is a time varying idiosyncratic element measuring the idiosyncratic distance between the common trend component, μ_t, and $y_{i,t}$. For any two series $y_{i,t}$ and $y_{j,t}$, Phillips and Sul (2007) define relative convergence in terms of their ratio so that relative convergence exists among the $y_{i,t}$ if

$$\lim_{t\to\infty} \frac{y_{i,t}}{y_{j,t}} = 1 \text{ for all } i \text{ and } j. \tag{15}$$

In terms of Equation (14), this condition is equivalent to convergence of the factor loading coefficients

$$\lim_{t\to\infty} \delta_{i,t} = \delta \text{ for all } i. \tag{16}$$

In the general case of Equation (14), since the total number of unknowns is greater than the number of observations in the panel, it is impossible to estimate the time varying loading coefficients, $\delta_{i,t}$, directly unless some structural restrictions are imposed on $\delta_{i,t}$ and μ_t. As a result, Phillips and Sul (2007) suggested that since μ_t is a common component in Equation (14), it may be removed by scaling to obtain the relative transition or loading coefficient,

$$h_{i,t} = \frac{y_{i,t}}{\frac{1}{N}\sum_{i=1}^{N} y_{i,t}} = \frac{\delta_{i,t}}{\frac{1}{N}\sum_{i=1}^{N} \delta_{i,t}}, \tag{17}$$

which measures the loading coefficient, $\delta_{i,t}$, relative to the panel average at time t. Intuitively, the relative transition parameter $h_{i,t}$ traces out a transition path for country i in relation to the panel average at time t. By definition, the cross sectional mean of $h_{i,t}$ is unity. In addition, the relative transition parameters $h_{i,t}$ converge to unity if the factor loading coefficients, $\delta_{i,t}$, converge to δ. In this case, the cross sectional variance of $h_{i,t}$ in the long run converges to zero, so that

$$\sigma_t^2 = \frac{1}{N}\sum_{i=1}^{N} (h_{i,t} - 1)^2 \to 0 \text{ as } t \to \infty. \tag{18}$$

To formulate a null hypothesis of convergence, Phillips and Sul (2007) use a semiparametric model for the loading coefficients $\delta_{i,t}$

$$\delta_{i,t} = \delta_i + \sigma_{i,t}\xi_{i,t}, \quad \sigma_{i,t} = \frac{\sigma_i}{L(t)t^{\alpha}}, \quad t \geq 1, \quad \sigma_i > 0 \quad \text{for all } i, \tag{19}$$

where δ_i is fixed, $\xi_{i,t}$ is $iid(0,1)$ across i, and $L(t)$ is a slowly varying functions such as log t that vary over i, and α governs the speed at which the cross sectional variation decays to zero over time. This formulation ensures that $\delta_{i,t}$ converges to δ_i for all $\alpha \geq 0$. If this condition holds and $\delta_i = \delta_j$ for $i \neq j$, the model allows for transitional periods in which $\delta_{i,t} \neq \delta_{j,t}$,

thereby incorporating any potential transitional heterogeneity across i. The conditions for convergence in the model can be summarized as

$$\begin{aligned} \lim_{t\to\infty} \delta_{i,t} = \delta \quad &\text{iff} \quad \delta_i = \delta \quad \text{and } \alpha \geq 0, \\ \lim_{t\to\infty} \delta_{i,t} \neq \delta \quad &\text{iff} \quad \delta_i \neq \delta \quad \text{and } \alpha < 0. \end{aligned} \tag{20}$$

The null and alternative hypotheses of convergence can now be formulated as

$$\begin{aligned} H_0 : \delta_i = \delta \quad &\text{and } \alpha \geq 0, \\ H_A : \delta_i \neq \delta \quad &\text{and } \alpha < 0. \end{aligned} \tag{21}$$

To test the null hypothesis of convergence, first, Phillips and Sul (2007) constructed the cross sectional variance ratio, H_1/H_t, where H_t is defined as

$$H_t = \frac{1}{N}\sum_{i=1}^{N}(h_{i,t}-1)^2, \quad h_{i,t} = \frac{y_{i,t}}{\frac{1}{N}\sum\limits_{i=1}^{N} y_{i,t}}. \tag{22}$$

H_1 represents the variation at the beginning of the sample and H_t represents the variation for $(t = 1, \ldots, T)$. Second, run the following log t regression

$$log\left(\frac{H_1}{H_t}\right) - 2\,log(log\,t) = \hat{a} + \hat{b}\,log\,t + \hat{u}_t, \quad \text{for } t = [rT], [rT]+1, \ldots T \quad \text{with } r > 0. \tag{23}$$

In Equation (23), as recommended by Phillips and Sul (2007), the data for this regression start at the integer part of $t = [rT]$, where $r = 0.3$, so the first $r\%$ of the data is discarded. The term $-2\,log(log\,t)$ serves as penalty function.[31] The fitted coefficient of log t is $\hat{b} = 2\,\hat{\alpha}$, where $\hat{\alpha}$ is the estimate of α in H_0. Finally, the t-statistic is constructed using heteroskedasticity and autocorrelation consistent (HAC) standard errors. By using the conventional t-statistic $t_{\hat{b}}$, the null hypothesis of convergence is rejected if $t_{\hat{b}} < -1.65$ at the 5

percent level.

3.1.3. Club clustering

Rejection of overall convergence does not rule out the possibility of club convergence. Accordingly, to investigate the possibility of a club convergence patterns, Phillips and Sul (2007) proposed a clustering algorithm test procedure. In this section, I briefly outline the basic steps for implementing the clustering procedure.

Step 1 (cross-section ordering): Order the countries according to the last observation in the panel.

Step 2 (core group formation): Identify a core group of countries that converge by selecting the first k highest countries in the panel to form the subgroup G_k for some $N > k \geq 2$ and then run the log t regression and compute the convergence test statistic $t_k = t(G_k)$ for this subgroup. Choose the core group size $k*$ by maximizing t_k over k; that is, keep adding countries to the core group until the null hypothesis of the log t test is rejected. If the condition $t(G_k < 1.65)$ does not hold for the $k = 2$ then the highest country in G_k can be dropped from each subgroup. Continue identifying additional subgroups within the entire panel.

Step 3 (club membership) Let G^c_{k*} be a complementary set to the core group G_{k*}. Add one country at a time from G^c_{k*} to the core group with $k*$ members identified in (Step 2) and then run the log t regression. Let $\hat{t}$ be the corresponding t statistic. Include the new country in the convergence club if the corresponding t-statistic $\hat{t}$ is greater than c, where $c \geq 0$ is some chosen critical value.

Step 4 (recursion and stopping): Form a subgroup from the countries not selected in the club formed in Step 3. Run the log t test for this set of countries to see if this complement group satisfies the convergence test. If it converges, then these countries form a second

convergence club, so that we have two convergence clubs. If not, Step 1 through Step 3 is repeated to see if there is evidence of subconvergence clusters in this second group. If no core group is found (Step 2), then these countries exhibit divergent behavior.

3.2. Linear dynamic model

In this section, I investigate whether the growth effect of FDI differs substantially across more homogenous group of countries. I use linear dynamic growth model to explore the FDI-finance-growth relationship across convergence clubs. To test for potential coefficient changes across clubs, within each group of countries, I estimate the following cross-country growth equation:

$$y_{i,t} - y_{i,t-1} = (\alpha - 1)y_{i,t-1} + \beta' X_{i,t} + \mu_i + \varepsilon_{i,t}. \tag{24}$$

where $y_{i,t}$ is the logarithm of real per capita GDP in country i at time t, and $X_{i,t}$ is a set of explanatory variables, including FDI, average years of schooling, government consumption expenditure, inflation rate, and trade openness, μ_i represents time invariant country-specific effect, and $\varepsilon_{i,t}$ denotes the idiosyncratic shocks.[32] All variables, with the exception of inflation, are transformed into logarithms. "Too much" finance implies that the estimated coefficient for FDI will be less positive in the clubs with larger average level of financial development. To obtain efficient, unbiased, and consistent estimates of the effect of FDI on growth, I use the system dynamic panel GMM estimator by Arellano and Bover (1995) and Blundell and Bond (1998).[33] This dynamic panel estimator has a number of advantages over cross-sectional estimators. First, the system dynamic panel GMM estimator addresses the potential endogeneity of all explanatory variables. Second, it accounts for the biases induced by including lagged or initial income in the growth equation. Third, unlike pure cross-sectional instrumental variable estimators, dynamic panel GMM estimator exploits the time series variation and controls for unobserved country-specific effect.

Rewrite Equation (24) as

$$y_{i,t} = \alpha y_{i,t-1} + \beta' X_{i,t} + \mu_i + \varepsilon_{i,t}. \tag{25}$$

To eliminate the unobserved country-specific effects, Holtz-Eakin et al. (1988) and Arellano and Bond (1991) suggest to first-difference Equation (25) as follows:

$$y_{i,t} - y_{i,t-1} = \alpha(y_{i,t-1} - y_{i,t-2}) + \beta'(X_{i,t} - X_{i,t-1}) + (\varepsilon_{i,t} - \varepsilon_{i,t-1}). \tag{26}$$

By construction, in Equation (26), the differenced lagged dependent variable $(y_{i,t-1} - y_{i,t-2})$ is correlated with the new error term $(\varepsilon_{i,t} - \varepsilon_{i,t-1})$: the former contains $y_{i,t-1}$ and the latter, now an MA(1) process, contains $\varepsilon_{i,t-1}$. To address this correlation and the potential endogeneity of the explanatory variables, Arellano and Bond (1991) suggest using the lagged levels of the explanatory variables as instruments under the assumptions that the error term, ε, is not serially correlated and that the explanatory variables are weakly exogenous[34]. Under these assumptions, this dynamic panel estimator, commonly referred to as *difference* GMM estimator, uses the following moment conditions:

$$E[y_{i,t-l}(\varepsilon_{i,t} - \varepsilon_{i,t-1})] = 0 \text{ for } l \geq 2;\ t = 3, \ldots, T. \tag{27}$$

$$E[X_{i,t-l}(\varepsilon_{i,t} - \varepsilon_{i,t-1})] = 0 \text{ for } l \geq 2;\ t = 3, \ldots, T. \tag{28}$$

The *difference* GMM estimator, however, has conceptual and statistical shortcomings. For example, Blundell and Bond (1998) and Alonso-Borrego and Arellano (1999) demonstrated that persistence in the lag dependent and explanatory variables makes lagged levels of these variables weak instruments for the differenced variables and this may adversely affect the small-sample and asymptotic properties of the difference GMM estimator. To

address this weak instrument problem and to improve efficiency, Arellano and Bover (1995) and Blundell and Bond (1998) proposed the *system* GMM estimator. The *system* GMM estimator augments the *difference* estimator by jointly estimating the regression in differences and the regression in levels. The two equations are distinctly instrumented. While the instruments for the regression in differences are the lagged levels of the explanatory variables (same as above), the instruments for the equation in levels are the lagged differences of the explanatory variables.

These instruments are valid under the additional assumption that the correlation between the country-specific effect, μ_i, and the levels of the explanatory variables is time-invariant, such that

$$E[y_{i,t+p}\mu_i] = E[y_{i,t+q}\mu_i] \text{ and } E[X_{i,t+p}\mu_i] = E[X_{i,t+q}\mu_i] \text{ for all } p \text{ and } q. \tag{29}$$

Given this assumption, there is no correlation between the country-specific effect, μ_i, and the differences of the explanatory variables. This assumption implies, for example, that any correlation between FDI or financial development and the country-specific effect is constant over time. Thus, the lagged differences of the explanatory variables are valid instruments for the equation in levels, and the additional moment conditions for the regression in levels are:

$$E[(y_{i,t-l} - y_{i,t-l-1})(\mu_i + \varepsilon_{i,t})] = 0 \text{ for } l = 1 \tag{30}$$

$$E[(X_{i,t-l} - X_{i,t-l-1})(\mu_i + \varepsilon_{i,t})] = 0 \text{ for } l = 1. \tag{31}$$

The *system* GMM thus consists of regressions in differences and levels stacked together. The *system* GMM estimator uses the moment conditions in Equations (27), (28), (30) and (31) to obtain consistent and efficient estimates. The moment conditions in Equations (27) and (28) are used in the first part of the system (regressions in differences) while the moment condi-

tions in Equations (30) and (31) are used in the second part of the system (regressions in levels). As with other GMM estimators, the *system* GMM have one- and two-step variants. Although asymptotically more efficient and robust to heteroscedasticity, the two-step *system* GMM estimation of the standard errors tend to be severely downward biased in finite samples. To eliminate this potential bias, I use the finite sample correction for the two-step covariance matrix derived by Windmeijer (2005).[35]

The consistency of the *system* GMM estimator relies on the validity of the instruments and the assumption that the error term, ε, is not serially correlated. Although, by construction, the residuals in first differences (AR(1)) are likely to be serially correlated, there should be no second-order, AR(2), serial correlation. I use two specification tests proposed by Arellano and Bond (1991) and Blundell and Bond (1998) to test these two assumptions. Hansen test of over-identifying restrictions is used to test the overall validity of the instruments.[36] The second test examines the hypothesis that the differenced error term is not second-order serially correlated.[37][38] Also, Roodman (2009) observed that instrument proliferation can result in biased parameter estimates. To reduce this instrument count problem, I "collapse" the instrument matrix in order to keep the number of instruments far below the number of countries.[39] In summary, I estimate the cross-country growth model using the two-step *system* GMM estimator with Windmeijer's (2005) finite sample correction for the covariance matrix.

3.3. Dynamic panel threshold model

To examine whether there is a common financial development threshold beyond which the positive effect of FDI on economic growth changes in magnitude, I use a dynamic panel threshold technique by Kremer et al. (2013) to test for threshold effect in the FDI-finance-growth relationship for each club.[40] This method extends the original model by Hansen

(1999) and Caner and Hansen (2004) to allow for endogenous regressors in a panel framework. If financial development plays a role in mediating the growth effect of FDI, regression functions will differ across clubs. The dynamic panel threshold model of the FDI-finance-growth nexus takes the following form:

$$\begin{aligned} Growth = \mu_i + \beta_1 FDI_{i,t} I(FIN_{i,t} \leq \gamma) + \delta I(FIN_{i,t} \leq \gamma) \\ + \beta_2 FDI_{i,t} I(FIN_{i,t} > \gamma) + \psi' X_{i,t} + \varepsilon_{i,t} \end{aligned} \tag{32}$$

where $Growth$ is the growth rate of real per capita GDP in country i at time t, μ_i is the country-specific fixed effect, γ is the threshold level, and the error term is $\varepsilon_{i,t} \overset{i.i.d}{\sim} (0, \sigma^2)$. $I(\cdot)$ is an indicator function taking a value of 1 if the argument in the indicator function holds, and 0 otherwise. The threshold variable, $FIN_{i,t}$, divides the sample into regimes with differing regression slope parameters β_1 and β_2. The level of financial development measured by private credit is used as the threshold variable. $X_{i,t}$ is a vector of explanatory variables which can be partitioned into a subset of exogenous variables ($X_{1i,t} = schooling$, $government\ expenditure$, $inflation\ rate$, $trade\ openness$) uncorrelated with $\varepsilon_{i,t}$, and a subset of endogenous variable ($X_{2i,t} = real\ per\ capita\ GDP\ from\ previous\ period$) correlated with $\varepsilon_{i,t}$. Allowing for differences in the regime intercept helps minimize any potential bias in both the threshold and the corresponding marginal effect estimates. Following Bick (2010), I include a threshold intercept, δ.[41] All variables, with the exception of inflation and growth, are transformed into logarithms.

Since the threshold level, γ, is not known a priori, it must be estimated. The estimation procedure involves eliminating the country-specific fixed effects μ_i using a fixed-effect transformation method. In a dynamic panel threshold model, however, the traditional within-transformation and first differencing methods of removing individual effects leads to inconsistent estimates as it violates the distributional assumptions underlying the threshold

model by Hansen (1999). Thus, the forward orthogonal deviations transformation method by Arellano and Bover (1995) is used to eliminate the country-specific fixed effects.[42] The estimation procedure by Caner and Hansen (2004) can then be applied to Equation (32).[43]

Following Caner and Hansen (2004), the parameters are estimated sequentially. First, I run a reduced-form regression of the endogenous variable $X_{2,it}$ on a set of instruments $Z_{1,it}$, including all exogenous regressors $X_{1i,t}$. I then obtain the predicted values $\hat{X}_{2,it}$. Second, in Equation (32), I replace $X_{2,it}$ with $\hat{X}_{2,it}$ and obtain the least square estimates for a fixed threshold γ. Let $S(\gamma)$ denote the resulting sum of squared residuals. For a strict subset of the support of $FIN_{i,t}$, I repeat this second step. Observe that, since the slope parameters depend on the threshold value, the sum of squared errors (SSE) for Equation (32) which is also a function of the threshold value is a step function, with the steps occurring at some well-defined values of the threshold variable $FIN_{i,t}$. Conditioning on a threshold value, however, SSE is linear in the parameters and minimization will yield the conditional OLS estimates for β_1 and β_2. Finally, the estimator of the threshold corresponds to the value of γ that produces the smallest sum of squared residuals. That is, the minimizer of the sum of squared residuals: $\hat{\gamma} = \underset{\gamma}{\operatorname{argmin}}\, S_n(\gamma)$.[44]

Let $C(\alpha)$ be the 95% percentile of the asymptotic distribution of the likelihood ratio statistic $LR(\gamma)$, then the critical values for determining the 95 percent confidence interval of the threshold value are given by $\Gamma = \{\gamma : LR(\gamma) \leq C(\alpha)\}$ (Hansen, 1999; Caner and Hansen, 2004). Once the sample-splitting threshold estimate $\hat{\gamma}$ is obtained, the sample can be divided into subsamples and, on each subsample, the slope parameters β_1 and β_2 can be estimated by generalized method of moments (GMM). Lags of the dependent variable are used as instruments. Given the bias-efficiency tradeoff in finite sample, empirical results based on GMM may depend on the number of instruments (Windmeijer, 2005; Roodman, 2009). Therefore, in estimation, I use different lag lengths. To avoid potential overfitting, I use a lag length of one, and to increase efficiency, I use all available lags as instruments.

However, the choice of instruments did not have any significant effect on the main results. In the results reported in this paper, I use an instrument count of two.

4. Empirical results

4.1. Transition curves and convergence clubs

There is a reasonable prior support for heterogeneous technological progress across countries. Thus, there is the possibility of diverse patterns of economic transition. As a starting exercise, I provide some graphical illustrations of the relative transition curves and the different phases of transition in the data.[45] Figure 3 shows the relative transition parameters for log private credit (top panel) and log real per capita GDP (bottom panel) in the 62 countries over the period 1984-2016.[46] It can be seen from Figure 3 that the relative transition curves display considerable heterogeneity. There appears to be no clear evidence supporting overall convergence since the relative transition curves show minimal reduction in dispersion over the sample period. In general, the pattern of economic transition and convergence can vary across countries or groups of countries. However, from Figure 3, visually identifying such potential distinctions appears impossible. As a result, to evaluate the transition curves and to shed light on convergence and convergence clustering, I use the log t convergence test.

Table 7 reports the results of applying the log t test to the full panel and four different subsamples. The table reports the point estimates, $\hat{b}$, and the corresponding t-statistics, $t_{\hat{b}}$, from estimating the log t regression equation (Equation (23)). I estimate two separate log t regressions, one using log private credit and the other using log real per capita GDP. For the full sample, the null hypothesis of overall financial development convergence is rejected at the 5% level ($t_{\hat{b}} = -5.776$). Similarly, the null hypothesis of overall income convergence is

rejected at the 5% level ($t_{\hat{b}} = -18.617$). Consistent with the observations from the relative transition curves in Figure 3, these results suggest that there is little evidence of overall financial development or income convergence among the 62 countries.

A substantial body of literature tends to use conventional classification of countries to examine heterogeneity. To examine convergence among members of these conventional groups, I perform separate analysis for each subsample. I apply the log t test to high income, middle income, OECD, and Non-OECD subsamples. Table 7 shows the log t test results for each group. The null hypothesis of overall financial development convergence is rejected for the high income and Non-OECD subsamples at the 5% level. However, for the middle income and OECD subsamples, there is some evidence of financial development convergence as we fail to reject the null hypothesis. With respect to income convergence, the point estimates, $\hat{b}$, are all negatives and the corresponding t-statistics $t_{\hat{b}}$ are large enough so that, at the 5% level, the null hypothesis of income convergence is consistently rejected in each subsample. In sum, there is little evidence of financial development or income convergence among member countries of these conventional groups, suggesting that these conventional classification of countries may not be the ideal way to capture the potential differential growth effect of FDI.

Given the lack of overall convergence and the fact that conventional subgroups of countries are not necessarily convergence clubs, to examine the FDI-finance-growth relationship within and across a more homogeneous group of countries, I apply the clustering algorithm proposed by Phillips and Sul (2007) to investigate the possibility of a club convergence pattern among the 62 countries. This method allows for transitional dynamics and individual heterogeneity and thus avoid ad hoc sample splitting.

Table 8 shows the club convergence results from applying the clustering procedures to the private credit panel of 62 countries. Based on private credit, the algorithm classifies the country data into two convergence clubs. In each club, the fitted log t regression coefficient is

significantly positive, revealing evidence of convergence. Club 1 consists of 51 countries while Club 2 is made up of 11 countries. Club 1 contains the most financially developed countries. The average private credit over the sample period is higher in Club 1 (72%) than in Club 2 (26%). In addition, the average real per capita GDP over the sample period is higher in Club 1 ($\approx$ \$20,577) than in Club 2 ($\approx$ \$4,401). Figure 4 shows the relative transition parameters for Club 1 (top panel) and Club 2 (bottom panel). The relative transition curves in each club appear to narrow toward unity toward the end of the sample period, supporting convergence.

Table 9 shows the club convergence results from the convergence test for real per capita GDP for the panel of 62 countries. Initially, the algorithm classifies the country data into six convergence clubs and a divergent group consisting of two countries. The fitted log t regression coefficient is significantly positive for clubs 1 through 6, revealing an evidence supporting club classification. However, the fitted coefficient is significantly negative for Group 7 and so the null hypothesis of convergence is rejected. In the middle panel of Table 9, I test for potential club merging. As seen in Table 9, with the exception of Clubs 2, 3, and 4, there appears to be no evidence supporting club merging. Hence, as shown in the right panel ('Final classification'), Clubs 1, 5, 6, and the aggregate of Clubs 2, 3, and 4 are considered to form separate convergence clubs. Table 10 displays the final four income convergence clubs, one divergent group, and member countries. The average private credit over the sample period is highest in Club 1 (106%) and lowest in Club 4 (22%). Similarly, the average real per capita GDP over the sample period is highest in Club 1 and decreases through Club 4. Figure 5 shows the relative transition parameters for Club 1 through Club 3.[47] The relative transition curves in each club show noticeable reduction in dispersion and appear to narrow toward unity at the end of the sample period, supporting convergence.

In sum, the results based on the convergence test show no evidence supporting a single long run equilibrium. However, there is some evidence of convergence clustering among

two different financial development convergence clubs and four different income clubs. An important feature from the clustering analysis is that club members are not necessarily geographically neighboring, and neither does income convergence necessarily imply financial development convergence. The goal of this paper is to explore the FDI-finance-growth relationship within and across convergence clubs. While, in this paper, I explore the general characteristics of the FDI-finance-growth relationship within and across convergence clubs, I do not examine the many possible determining factors in each club.

4.2. Linear dynamic model

In this section, I examine the relationship between FDI and economic growth for each convergence club. To test for potential coefficient changes across convergence clubs, within each club of countries, I estimate the linear dynamic model Equation (24) using the two-step *system* GMM estimator with Windmeijer's (2005) finite sample correction. The data used for the estimation are averaged over 3-year non-overlapping periods. Table 11 presents these results. For comparison purposes, I also report the results for the full sample of 62 countries. The estimated coefficient of FDI for the full sample is significantly positive at the 1% level, suggesting that FDI has direct effect on growth. Regarding the two financial development clubs, the estimated coefficients of FDI for both clubs are significantly positive. However, the coefficient appears to be substantially lower in for Club 1 than in Club 2. The coefficient difference is statistically significant at 5% level. Similarly, for the three income clubs, the coefficient of FDI increases as we move from Club 1 to Club 3. In income Club 1, the coefficient is positive and significantly different from zero. The coefficient for Club 3 (0.735) is also significantly positive but appears larger in magnitude than that in Club 2 (0.139). Also, relative to the full sample, the growth effect of FDI in Club 2 is larger but smaller in Club 1.

As a sensitivity analysis, Table 12 presents the estimation results from Equation (24) using 5-year average data. The results are qualitatively similar to those obtained in Table 11. With the exception of income Club 2, the estimated coefficient in each club is significantly positive albeit it differs across clubs. As seen in Tables 11 and 12, the estimated coefficient of initial income is mostly negative. This is consistent with β-convergence. All the other explanatory variables have the expected signs whenever significant. Also, the Arellano-Bond serial correlation test shows that there is no second-order serial correlation while the Hansen instrument validity test shows the instruments are not correlated with the error term.

Overall, the growth effect of FDI displays heterogeneity across convergence clubs, appearing to be smaller in clubs with higher average financial development. The results point to the presence of potential nonlinearity or threshold effects in the FDI-finance-growth relationship. The implication is that more finance is not always better. The more financially developed a country is, the smaller the effect of FDI on growth. In addition, the level of development of a country matters. These findings are consistent with the diminishing returns effects observed in the literature (see, for example, Rioja and Valev, 2004a,b; Aghion et al., 2005; Shen and Lee, 2006; Rousseau and Wachtel, 2011; Arcand et al., 2015).

4.3. Dynamic panel threshold model

To test for the existence of a common financial development threshold beyond which the positive effect of FDI on economic growth changes in magnitude, Table 13 presents the estimates from the dynamic panel threshold model (Equation (32)) for the full sample and the two financial development clubs. Each column shows the coefficient from a separate regression using 3-year average data.[48] Private credit is used as the threshold variable. To examine the sensitivity of the benchmark results, following the literature (Levine et al., 2000; Beck et al., 2000), for each club, I report estimates using "simple" conditioning set that

includes only the logarithm of initial income and educational attainment. The first row of Table 13 displays the estimated financial development threshold values and the corresponding 95% confidence intervals. The slope parameter estimates, $\hat{\beta}_1$ and $\hat{\beta}_2$, denote the regime-dependent marginal effects of FDI on growth.

The point estimate of the threshold value for Club 1 is 92.58% of GDP with a 95% confidence interval lying between 83.75% and 97.49%. The literature on the FDI-finance-growth relationship has not considered the upper financial development threshold effects, thus limiting comparisons. Regarding the regime-dependent marginal effects, FDI has significantly positive effect on economic growth if private credit is less than the threshold. Above the threshold value, however, FDI appears to have no significant effect on growth. This is consistent with the diminishing returns effects in the development of financial sector. The threshold value remains unchanged albeit the marginal effects are relatively larger when the "simple" conditioning set is used for the estimation. For Club 2, the point estimate of the threshold value is 10.95% of GDP and the 95% confidence interval lies between 10.43% and 17.07%.

In contrast to Club 1, in Club 2, FDI has significantly positive effect on economic growth if private credit is greater than the threshold. However, below this threshold value, FDI appears to have no significant effect on growth. The results remain robust to the "simple" conditioning set. This suggest that a minimum level of financial development threshold is required for FDI to have positive effect on economic growth of a country. Rioja and Valev (2004a) find that finance has positive effect on growth when private credit to GDP is greater than 14%. Notice that when Club 1 and Club 2 are pooled together (full sample), one threshold value exist. By separating the full sample into clubs, two thresholds values are identified, lower and upper thresholds. All the "policy covariates are plausibly signed where significant.

For further robustness checks, I reestimate the model using 5-year average data. The

results are reported in Table 14. The results are qualitatively similar to the results obtained using 3-year average data. In particular, I find both upper and lower thresholds. Moving away from the financial development convergence clubs, I estimate the model for each income convergence club using 3-year average data. Table 15 presents the estimates from the dynamic panel threshold model (Equation (32)) for the three income clubs. I find evidence of threshold effects in Clubs 1 and 2. In Club 1, the point estimate of the threshold value is 53.96% [43.59-108.08%] and the slope estimates are both positive and statistically significant. However, above the threshold, the effect of FDI on growth is smaller. The threshold value for Club 2 is 92.58% of GDP with a 95% confidence interval lying between 88.06% and 100.47%. FDI appears to have no significant effect on growth above the threshold value but the effect is positive and statistically significant below the threshold. There is no evidence of threshold effect in Club 3. Unlike the threshold analysis based on the financial development clubs, the confidence intervals in the case of the income clubs are wide and tend to overlap.

The empirical findings point to the presence of threshold effects in the FDI-finance-growth relationship. The positive effect of FDI on economic growth kicks in only after a country achieves a minimum level of financial development threshold. But there is also a financial development threshold beyond which the growth effect of FDI becomes negligible. These results are consistent with the diminishing returns effects in the development of financial sector (see, for example, Rioja and Valev, 2004a; Shen and Lee, 2006; Rousseau and Wachtel, 2011; Beck et al., 2014; Herwartz and Walle, 2014; Law and Singh, 2014; Arcand et al., 2015).

5. Conclusion

The consensus in the empirical macro literature is that the growth benefit of FDI is not automatic but conditional on host country policies and environments, including financial

sector development. The goal of this paper is to explore the FDI-finance-growth relationship within and across convergence clubs. For this purpose, I first apply the log t regression test for convergence and clustering proposed by Phillips and Sul (2007) to examine whether countries converge to a single long run equilibrium. In the second part, I examine whether the growth effect of FDI differs across convergence clubs using the two-step system generalized method of moments (GMM) estimator with Windmeijer's (2005) finite sample correction. In addition, I test for threshold effect in the FDI-finance-growth relationship for each club using a dynamic panel threshold technique. The empirical analysis is based on a panel of 62 middle and high income countries spanning the period 1987-2016.

I find evidence of convergence clustering among two different clubs based on financial development and four different clubs based on real per capita GDP. Overall, the growth effect of FDI displays substantial heterogeneity across convergence clubs, appearing to be smaller in clubs with higher average financial development. In addition, to a larger extent, the level of development of a country matters. The results also point to the presence of threshold effects. The positive effect of FDI on economic growth kicks in only after a country achieves a minimum level of financial development threshold. But there is also a financial development threshold beyond which the growth effect of FDI becomes negligible. These results are consistent with the diminishing returns effects in the development of financial sector.

This paper contributes to the growing literature on structural and policy related conditions that can affect the relationship between FDI inflows and economic growth by showing that heterogeneity and nonlinearity matter in this relationship. The findings from this paper suggest that at low levels of financial development, improving domestic financial sector conditions can help host economies maximized the growth benefit of FDI. However, consistent with the diminishing returns effects in the development of financial sector, the growth effect of FDI tends to decline as a country becomes more financially developed, suggesting that

more finance is not always better. In addition, to accurately examine the role of financial development in mediating the potential growth benefit of FDI, it is important for researchers and policymakers to allow for cross-country differences in financial development.

Notes

[1]The interaction between downstream and upstream firms is called the backward linkage channel. That is, interaction between the upstream domestic suppliers of intermediate inputs and their multinational clients. Domestic firms, through backward linkage channel, may obtain free knowledge transfer by being a supplier of intermediate input to multinational firms. By having a foreign upstream firms and gaining access to less costly intermediate inputs from foreign suppliers, domestic firms may become more productive - forward linkage channel.

[2]I use bank-based financial development because using stock-market-based measures reduce the sample substantially.

[3]For the financial institution index, 2014 was the most recent year of data available at the time of the analysis

[4]The 3-year non-overlapping periods are 1987-1989, 1990-1992, 1993-1995, 1996-1998, 1999-2001, 2002-2004, 2005-2007, 2008-2010, 2011-2013, and 2014-2016.

[5]Top half sample includes the 31 most financially developed countries with average level of private credit to GDP over the sample period exceeding 50 percent. The average level of private credit to GDP for the bottom half is 50 percent or less.

[6]In estimating Equation (1), I control for time-specific effect and any potential cross-sectional dependence by using cross-sectionally demeaned data for all variables.

[7]See Holtz-Eakin et al. (1988), Arellano and Bond (1991), Arellano and Bover (1995), Blundell and Bond (1998), and Roodman (2009) for a detailed description of the system dynamic panel GMM estimator.

[8]The explanatory variables are uncorrelated with future error terms.

[9]See Roodman (2009) for details.

[10]The null hypothesis is that the lagged differences of the explanatory variables are not correlated with the error term.

[11]The null hypothesis is that there is no second-order serial correlation.

[12]A consistent *system* GMM estimator fails to reject both null hypotheses.

[13]I use the "collapse" option in the xtabond2 STATA command. See Roodman (2009) for details.

[14]I do not use quadratic specification since it places a specific functional form on the nonlinearity regardless of the patterns in the data. Unlike other nonlinear models such as spline and quadratic regressions, the threshold model does not impose any specific functional form on the nonlinearity aspect of the model.

[15]Including time dummies to control for time-fixed effect did not change the main results.

[16]The forward orthogonal deviations transformation subtracts the average of all future available observations of a variable from each observation. This ensures the error terms are not correlated. See Kremer et al. (2013).

[17]I thank Alexander Bick for making the MATLAB code for the dynamic panel threshold estimation available online at `https://alexbick.weebly.com/publications.html`.

[18]This minimization problem can be reduced to searching over values of γ up to nT distinct values of $FIN_{i,t}$ in the sample.

[19]The results are robust to using 5-year averages and are available upon request.

[20]The World Bank defines middle income countries as those with a GNI per capita between $1,026 and $12,475 and high income countries as those with a GNI per capita of $12,476 or more.

[21]Private credit enters the model as log(private credit + 1).

[22]A multinational corporation would often rely on host-country financing in order to minimize overall cost of capital, reduce exposure to exchange rate risk, and gain access to liquid funds that would otherwise be tied up. Also, multinational firms tend to adjust the scale of operations when local financial institutions are more developed. See, for example, (Alfaro et al., 2004; Bilir et al., 2014) for anecdotal and systematic evidence.

[23]In a survey of 72 empirical macro studies on the growth effect of FDI, Bruno and Campos (2013) observe that 50 percent of the studies find positive growth effect, 11 percent find negative effect while 39 percent find no relationship between FDI and growth. For the 103 micro studies, the authors find 44 percent of the estimates are significantly positive, 44 percent are insignificant while 12 percent are significantly negative.

[24]Backward linkage involves the interaction between domestic suppliers of intermediate inputs and multinational clients in downstream sectors while forward linkage occurs between foreign suppliers of intermediate inputs and domestic clients in upstream sectors.

[25]I use the term income convergence and growth convergence interchangeably in this paper.

[26]Net FDI inflows measure the net inflows of investment to acquire a lasting interest (the foreign investor holds at least 10 percent or more of a local firms equity) in an enterprise operating in an economy outside of the investor's.

[27]Bank-based financial development are used because using stock-market-based measures reduce the sample substantially.

[28]The 3-year non-overlapping periods are 1987-1989, 1990-1992, 1993-1995, 1996-1998, 1999-2001, 2002-2004, 2005-2007, 2008-2010, 2011-2013, and 2014-2016.

[29]The unconditional OLS β coefficient estimate for the full sample is -0.009 with a standard error of 0.003.

[30]The World Bank defines middle-income countries as those with a GNI per capita between $1,026 and $12,475 and high-income countries as those with a GNI per capita of $12,476 or more.

[31]For example, under the alternative hypothesis of club convergence, this penalty term gives the test discriminatory power between overall convergence and club convergence.

[32]In estimating Equation (24), I control for time-specific effect and any potential cross-sectional dependence by using cross-sectionally demeaned data for all variables.

[33]See Holtz-Eakin et al. (1988), Arellano and Bond (1991), Arellano and Bover (1995), Blundell and Bond (1998), and Roodman (2009) for a detailed description of the system dynamic panel GMM estimator.

[34]The explanatory variables are uncorrelated with future error terms.

[35]See Roodman (2009) for details.

[36]The null hypothesis is that the lagged differences of the explanatory variables are not correlated with the error term.

[37]The null hypothesis is that there is no second-order serial correlation.

[38]A consistent *system* GMM estimator fails to reject both null hypotheses.

[39]I use the "collapse" option in the xtabond2 STATA command. See Roodman (2009) for details.

[40]I do not use quadratic specification since it places a specific functional form on the nonlinearity regardless of the patterns in the data. Unlike other nonlinear models such as spline and quadratic regressions, the threshold model does not impose any specific functional form on the nonlinearity aspect of the model.

[41]Including time dummies to control for time-fixed effect did not change the main results.

[42]The forward orthogonal deviations transformation subtracts the average of all future available observations of a variable from each observation. This ensures the error terms are not correlated. See Kremer et al. (2013).

[43]I thank Alexander Bick for making the MATLAB code for the dynamic panel threshold estimation available online at `https://alexbick.weebly.com/publications.html`.

[44]This minimization problem can be reduced to searching over values of γ up to nT distinct values of $FIN_{i,t}$ in the sample.

[45]I used the Stata codes provided by Du (2017) to perform the econometric convergence analysis and club clustering.

[46]Following Phillips and Sul (2007), I remove the business cycle components using the Hodrick-Prescott smoothing filter (Hodrick and Prescott, 1997).

[47]Since the sample size is relatively small in Club 4 and Group 5, I restrict further empirical investigations to Clubs 1, 2, and 3.

[48]The results are robust to using 5-year averages and are available upon request.

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Table 1. Descriptive statistics

	N	Mean	SD	Min	Max
Real GDP per capita growth	620	0.021	0.024	-0.074	0.108
Log real GDP per capita	620	8.996	1.393	5.959	11.41
Foreign direct investment	620	0.032	0.05	-0.058	0.567
Domestic investment	620	0.221	0.052	0.085	0.433
Private credit	620	0.639	0.487	0.023	2.683
Bank credit	620	0.59	0.44	0.023	2.683
Liquid liabilities	620	0.636	0.383	0.093	2.39
Financial institutions index	620	0.48	0.241	0.076	0.999
Government consumption	620	0.155	0.051	0.038	0.333
Openness	620	0.785	0.507	0.136	4.173
Inflation	620	0.074	0.123	-0.045	1.021
Average years of schooling	620	7.448	2.852	1.09	13.42

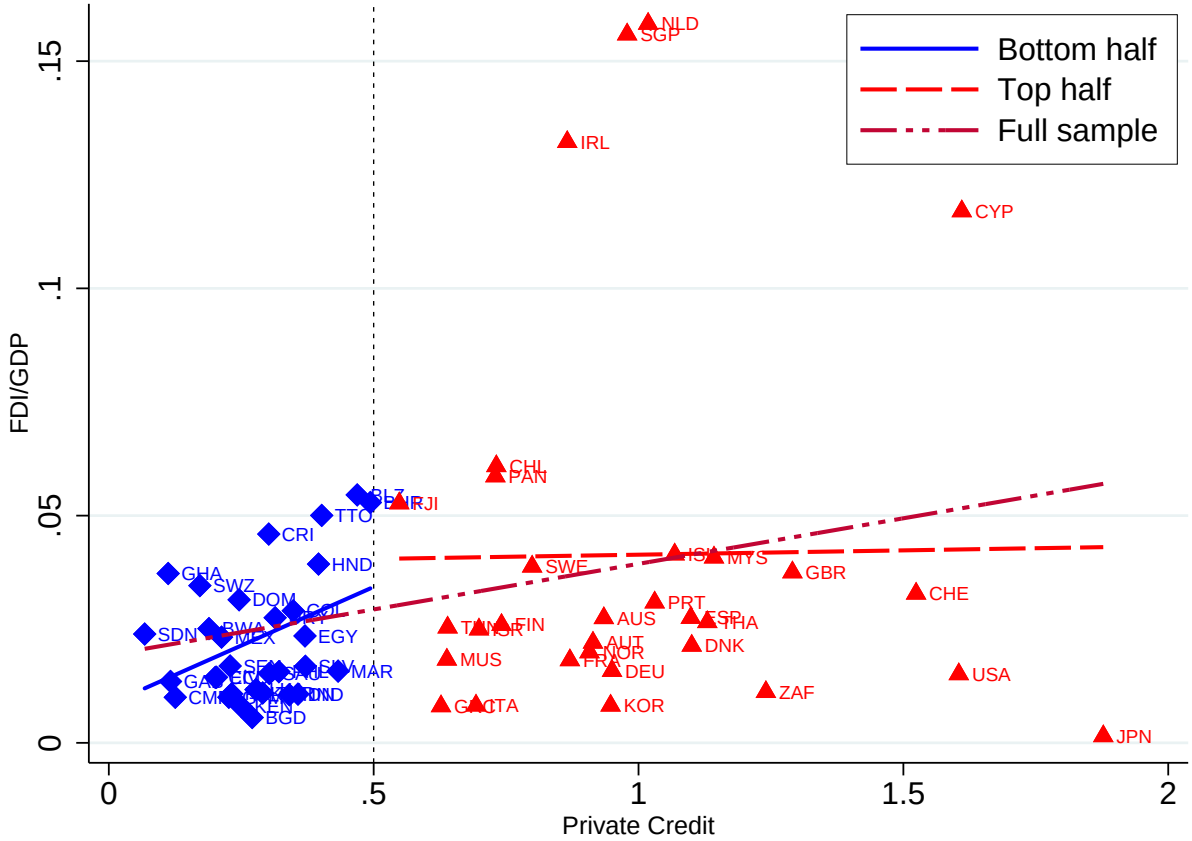

Figure 1. Average private credit to GDP and average FDI as a share of GDP, 1987-2016

Notes: Countries are ranked according to their average level of financial development measured by private credit to GDP over the sample period and then split into bottom half and top half subsamples. Top half sample includes the 31 most financially developed countries with average level of private credit to GDP over the sample period exceeding 50 percent. The average level of private credit to GDP for the bottom half is 50 percent or less.

Table 2. Correlation

	Full sample		Bottom half		Top half	
	Growth	FDI	Growth	FDI	Growth	FDI
FDI	0.179**	1	0.230**	1	0.185**	1
Private Credit	-0.092**	0.259**	-0.083	0.380**	-0.239**	0.159**

Notes: Top half sample includes the 31 most financially developed countries with average level of private credit to GDP over the sample period exceeding 50 percent. The average level of private credit to GDP for the bottom half is 50 percent or less.

Table 3. Growth effect of FDI: split-sample regressions

	Full sample	Two-way split		Three-way split		
		Bottom half	Top half	Bottom third	Middle third	Top third
Initial income	-0.061***	-0.051**	-0.129***	-0.009	-0.118***	-0.100***
	(0.014)	(0.021)	(0.023)	(0.018)	(0.020)	(0.034)
FDI	0.163***	0.234*	0.078***	0.321***	0.231***	0.194
	(0.058)	(0.117)	(0.021)	(0.105)	(0.053)	(0.197)
Gov't consumption	-0.305***	-0.075	-0.689***	-0.076	-0.592***	-0.428*
	(0.101)	(0.099)	(0.190)	(0.099)	(0.166)	(0.235)
Openness	0.063***	0.057*	0.079**	0.037	0.076	0.100**
	(0.022)	(0.032)	(0.034)	(0.030)	(0.045)	(0.046)
Inflation	-0.053***	-0.040**	-0.267***	-0.025*	-0.135**	-0.296***
	(0.015)	(0.017)	(0.067)	(0.013)	(0.058)	(0.066)
Schooling	0.027*	0.036	0.097**	0.016	0.101***	0.002
	(0.015)	(0.021)	(0.038)	(0.019)	(0.027)	(0.037)
Observations	620	310	310	210	210	200
Number of countries	62	31	31	21	21	20
Hansen test (P value)	0.729	0.243	0.614	0.755	0.575	0.382
AR(2) test (p-value)	0.122	0.388	0.462	0.681	0.144	0.386

Notes: Each column shows the coefficient from a separate regression. The estimation method is two-step system GMM with Windmeijer's (2005) finite-sample correction. All variables are cross-sectionally demeaned log values. Windmeijer (2005)-corrected cluster-robust standard errors are in parentheses. ***, **, and * indicates statistical significance at the 1% , 5%, and 10% level.

Table 4. Growth effect of FDI and the level of financial development

	Income group		Interaction		
	Middle income	High income	Private credit	Bank credit	Liquid liabilities
Initial income	-0.047**	-0.098***	-0.059***	-0.059***	-0.062***
	(0.023)	(0.029)	(0.011)	(0.011)	(0.011)
FDI	0.246**	0.084*	0.262***	0.271***	0.408***
	(0.110)	(0.044)	(0.070)	(0.075)	(0.128)
Gov't consumption	-0.174**	-0.396*	-0.270***	-0.266**	-0.235**
	(0.079)	(0.206)	(0.100)	(0.101)	(0.103)
Openness	0.021	0.156***	0.026	0.025	0.008
	(0.023)	(0.018)	(0.025)	(0.025)	(0.024)
Inflation	-0.055***	-0.052*	-0.050***	-0.049***	-0.046***
	(0.016)	(0.027)	(0.015)	(0.015)	(0.015)
Schooling	0.028	0.020	0.028**	0.029**	0.029**
	(0.026)	(0.041)	(0.013)	(0.013)	(0.014)
FDI*Private credit			-0.614*		
			(0.342)		
FDI*Bank credit				-0.671*	
				(0.351)	
FDI*Liquid liabilities					-1.210**
					(0.552)
F-statistic for FDI			7.60***	7.55***	5.77***
Observations	340	280	620	620	620
Number of countries	34	28	62	62	62
Hansen test (P value)	0.688	0.685	0.202	0.212	0.272
AR(2) test (p-value)	0.125	0.349	0.211	0.209	0.464

Notes: Each column shows the coefficient from a separate regression. The estimation method is two-step system GMM with Windmeijer's (2005) finite-sample correction. All variables are cross-sectionally demeaned log values. Windmeijer (2005)-corrected cluster-robust standard errors are in parentheses. In column 3, the interaction is between FDI and private credit; it is between FDI and bank credit in column 4; in column 5, it is between FDI and liquid liabilities. ***, **, and * indicates statistical significance at the 1% , 5%, and 10% level.

Table 5. Growth effects of FDI: dynamic threshold regression estimates

	Private credit	Bank credit	Liquid liabilities	Fin inst index
Threshold ($\hat{\gamma}$)	92.582	83.773	91.203	0.607
	[83.748-97.492]	[83.021-97.148]	[83.020-92.418]	[0.569-0.641]
Impact of FDI				
$\hat{\beta}_1 FDII(FD \leq \hat{\gamma})$	0.235***	0.234***	0.209***	0.282***
	(0.046)	(0.048)	(0.043)	(0.070)
$\hat{\beta}_2 FDII(FD > \hat{\gamma})$	0.033	0.025	0.086**	0.045
	(0.031)	(0.029)	(0.034)	(0.030)
Impact of covariates				
Initial Income	-0.025**	-0.026**	-0.026**	-0.029**
	(0.012)	(0.012)	(0.012)	(0.012)
Govt Consumption	-0.217***	-0.218***	-0.228***	-0.261***
	(0.069)	(0.069)	(0.070)	(0.072)
Openness	0.032**	0.033**	0.042***	0.036**
	(0.015)	(0.015)	(0.015)	(0.015)
Inflation	-0.035***	-0.035***	-0.036***	-0.038***
	(0.011)	(0.011)	(0.011)	(0.011)
Schooling	0.012	0.011	0.011	0.010
	(0.015)	(0.015)	(0.015)	(0.015)
$\hat{\delta}$	0.012***	0.013***	0.020***	0.010**
	(0.004)	(0.004)	(0.005)	(0.005)
Countries	62	62	62	62
Observations	620	620	620	620

Notes: Each column shows the coefficient from a separate regression. Standard errors are in parentheses. ***, **, and * indicates statistical significance at the 1% , 5%, and 10% level.

Table 6. Robustness: dynamic threshold regression estimates

	Private credit	Bank credit	Liquid liabilities	Fin inst index
Threshold ($\hat{\gamma}$)	92.58	83.773	91.204	0.615
	[83.748-96.511]	[83.370-94.137]	[83.185-95.255]	[0.569-0.641]
Impact of FDI				
$\hat{\beta}_1 FDII(FD \leq \hat{\gamma})$	0.279***	0.278***	0.248***	0.330***
	(0.049)	(0.050)	(0.048)	(0.074)
$\hat{\beta}_2 FDII(FD > \hat{\gamma})$	0.040	0.033	0.109***	0.062*
	(0.032)	(0.030)	(0.038)	(0.032)
Impact of covariates				
Initial Income	-0.024**	-0.025**	-0.024**	-0.028**
	(0.012)	(0.012)	(0.012)	(0.012)
Schooling	0.021	0.021	0.023	0.021
	(0.014)	(0.015)	(0.015)	(0.015)
$\hat{\delta}$	0.012***	0.014***	0.021***	0.010**
	(0.004)	(0.004)	(0.005)	(0.005)
Countries	62	62	62	62
Observations	620	620	620	620

Notes: Each column shows the coefficient from a separate regression. Standard errors are in parentheses. ***, **, and * indicates statistical significance at the 1% , 5%, and 10% level.

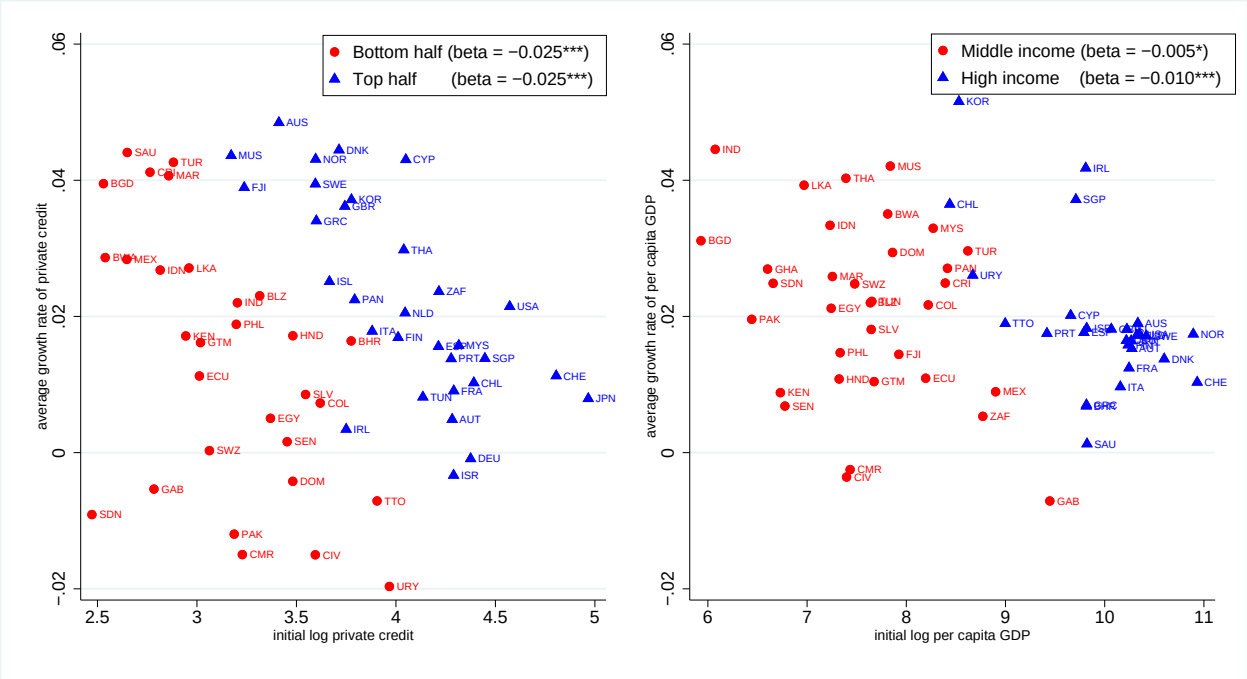

Figure 2. Growth of private credit and growth real per capita GDP

Notes: The left panel shows the relationship between initial log private credit and average growth rate of private credit for the full sample. The right panel shows the relationship between initial log per capita GDP and average growth rate of per capita GDP.

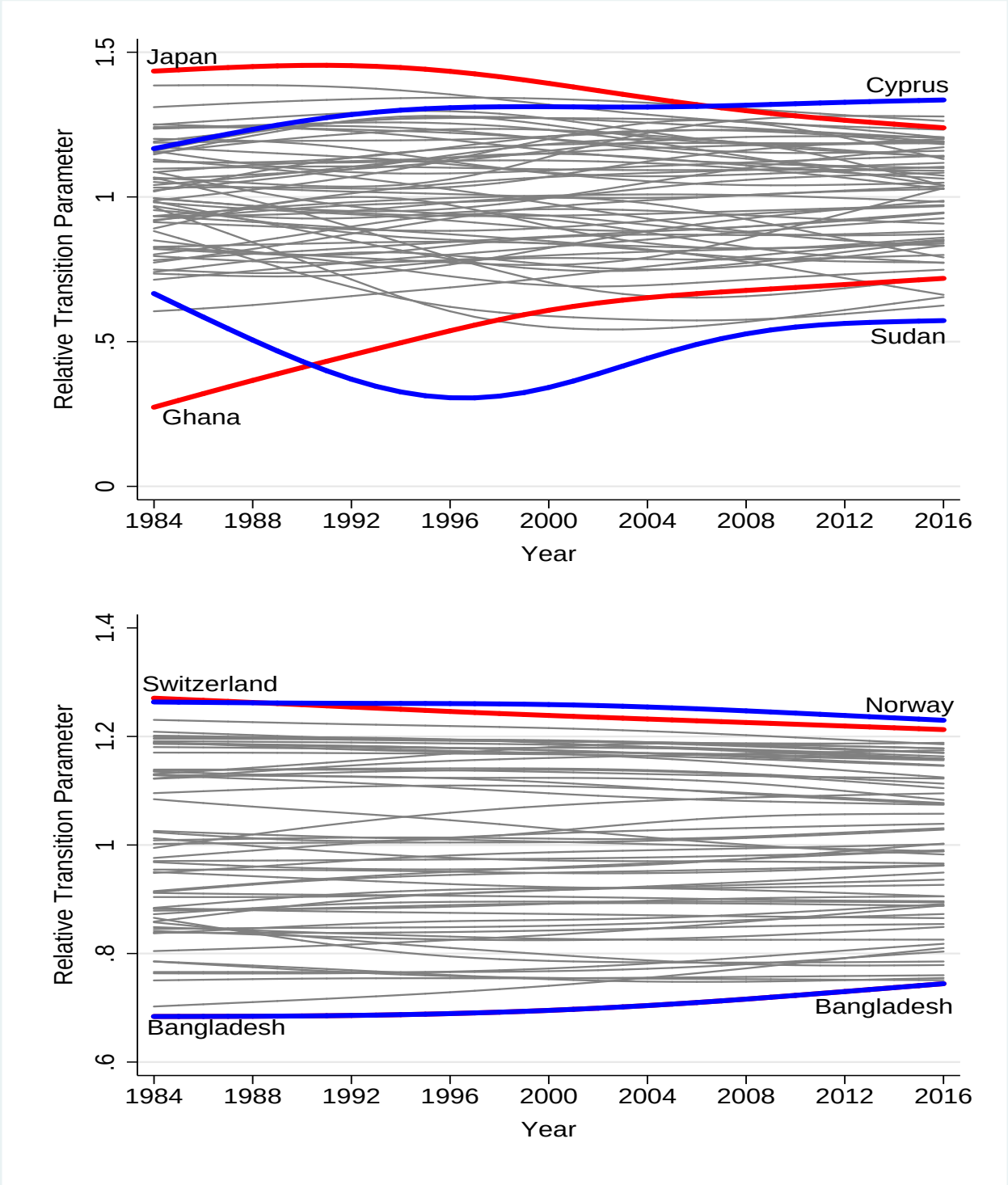

Figure 3. Relative transition curves for the 62 countries

Notes: Relative transition curves for the 62 countries. The top panel shows the relative transition curves of log private credit while the bottom panel shows the relative transition curves of log real per capita GDP.

Table 7. Convergence tests

	log private credit		log real per capita GDP	
Cases	$\hat{b}$	$t_{\hat{b}}$	$\hat{b}$	$t_{\hat{b}}$
Full sample (62)	-0.271	-5.776	-0.439	-18.617
High income (28)	-0.611	-27.599	-0.247	-11.105
Middle income (34)	-0.034	-0.445	-0.481	-20.601
OECD (24)	0.253	3.683	-0.352	-21.197
Non-OECD (38)	-0.176	-3.472	-0.468	-20.000

Notes: The columns report the point estimates $\hat{b}$ and the corresponding t-statistics $t_{\hat{b}}$ from estimating log t regression model. In the first two columns, log private credit is used while in columns (3) and (4), log real per capita GDP is used in the log t test.

Table 8. Convergence club classification: private credit

Club	$\hat{b}$	$t_{\hat{b}}$	Member countries	Average private credit	Average real per capita GDP
Club 1 [51]	0.154	2.558	Australia, Austria, Bahrain, Bangladesh, Belize, Botswana, Chile, Colombia, Costa Rica, Cyprus, Denmark, Ecuador, El Salvador, Fiji, Finland, France, Germany, Ghana, Greece, Guatemala, Honduras, Iceland, India, Ireland, Israel, Italy, Japan, Kenya, Korea, Rep., Malaysia, Mauritius, Mexico, Morocco, Netherlands, Norway, Panama, Portugal, Saudi Arabia, Senegal, Singapore, South Africa, Spain, Sri Lanka, Sudan, Sweden, Switzerland, Thailand, Tunisia, Turkey, United Kingdom, United States	0.721	$20577.295
Club 2 [11]	0.295	1.494	Cameroon, Cote d'Ivoire, Dominican Republic, Egypt, Arab Rep., Gabon, Indonesia, Pakistan, Philippines, Swaziland, Trinidad and Tobago, Uruguay	0.258	$4401.070

Notes: The numbers in brackets stand for the number of countries in a club.

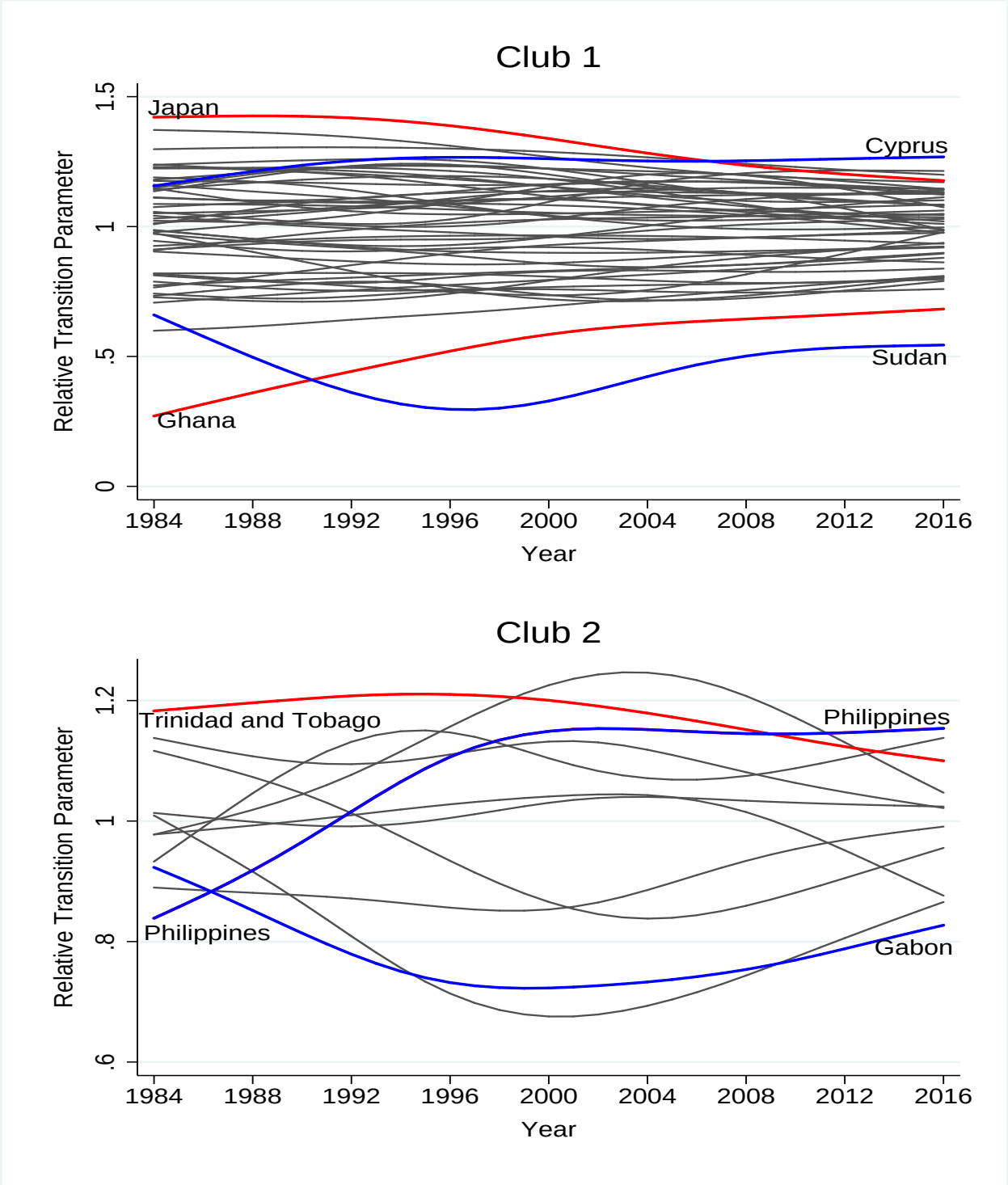

Figure 4. Relative transition curves for by convergence clubs

Notes: Relative transition curves of log private credit for the two clubs. The top panel shows the relative transition curves for countries in club 1 while the bottom panel shows the relative transition curves for countries in club 2.

Table 9. Convergence club classification: real per capita GDP

Initial classification $\hat{b}(t_{\hat{b}})$		Tests of club merging $\hat{b}(t_{\hat{b}})$						Final classification $\hat{b}(t_{\hat{b}})$	
Club 1 [17]	0.228	Club 1+2						Club 1 [17]	0.228
	(6.048)	-0.111**							(6.048)
Club 2 [13]	0.092	(-3.363)	Club 2+3						
	(2.072)		0.027						
Club 3 [6]	0.071		(0.639)	Club 3+4				Club 2 [22]	0.040
	(1.595)			0.082					(0.966)
Club 4 [3]	0.052			(1.937)	Club 4+5				
	(0.999)				-0.055**				
Club 5 [15]	0.132				(-1.413)	Club 5+6		Club 3 [15]	0.132
	(2.900)					-0.297**			(2.900)
Club 6 [6]	1.334					(-9.708)	Club 6+7	Club 4 [6]	1.334
	(14.656)						-0.063**		(14.656)
Group 7 [2]	-0.463						(-1.750)	Group 5 [2]	-0.463
	(-6.706)								(-6.706)

Notes: ** reject the null hypothesis of growth convergence at 5% level. The numbers in brackets stand for the number of countries in a club. Initial clustering consist of six subconvergence clubs and a divergent group. Tests of club merging lead to the final classification of four convergence clubs and a divergent group.

Table 10. Convergence club classification: real per capita GDP

Club	$\hat{b}$	$t_{\hat{b}}$	Member countries	Average private credit	Average real per capita GDP
Club 1 [17]	0.228	6.048	Australia, Austria, Denmark, Finland, Germany, Iceland, Ireland, Japan, Korea, Rep., Netherlands, Norway, Singapore, Sweden, Switzerland, Trinidad and Tobago, United Kingdom, United States	1.055	$42240.453
Club 2 [22]	0.040	0.966	Bahrain, Botswana, Chile, Colombia, Costa Rica, Cyprus, Dominican Republic, France, Greece, India, Israel, Italy, Malaysia, Mauritius, Panama, Portugal, Saudi Arabia, Spain, Sri Lanka, Thailand, Turkey, Uruguay	0.642	$14218.162
Club 3 [15]	0.132	2.900	Belize, Ecuador, Egypt, Arab Rep., El Salvador, Fiji, Gabon, Ghana, Indonesia, Mexico, Morocco, Philippines, South Africa, Sudan, Swaziland, Tunisia	0.374	$3779.421
Club 4 [6]	1.334	14.656	Bangladesh, Cameroon, Cote d'Ivoire, Kenya, Pakistan, Senegal	0.218	$991.708
Group 5 [2]	-0.463	-6.706	Guatemala, Honduras	0.311	$2162.452

Notes: The numbers in brackets stand for the number of countries in a club.

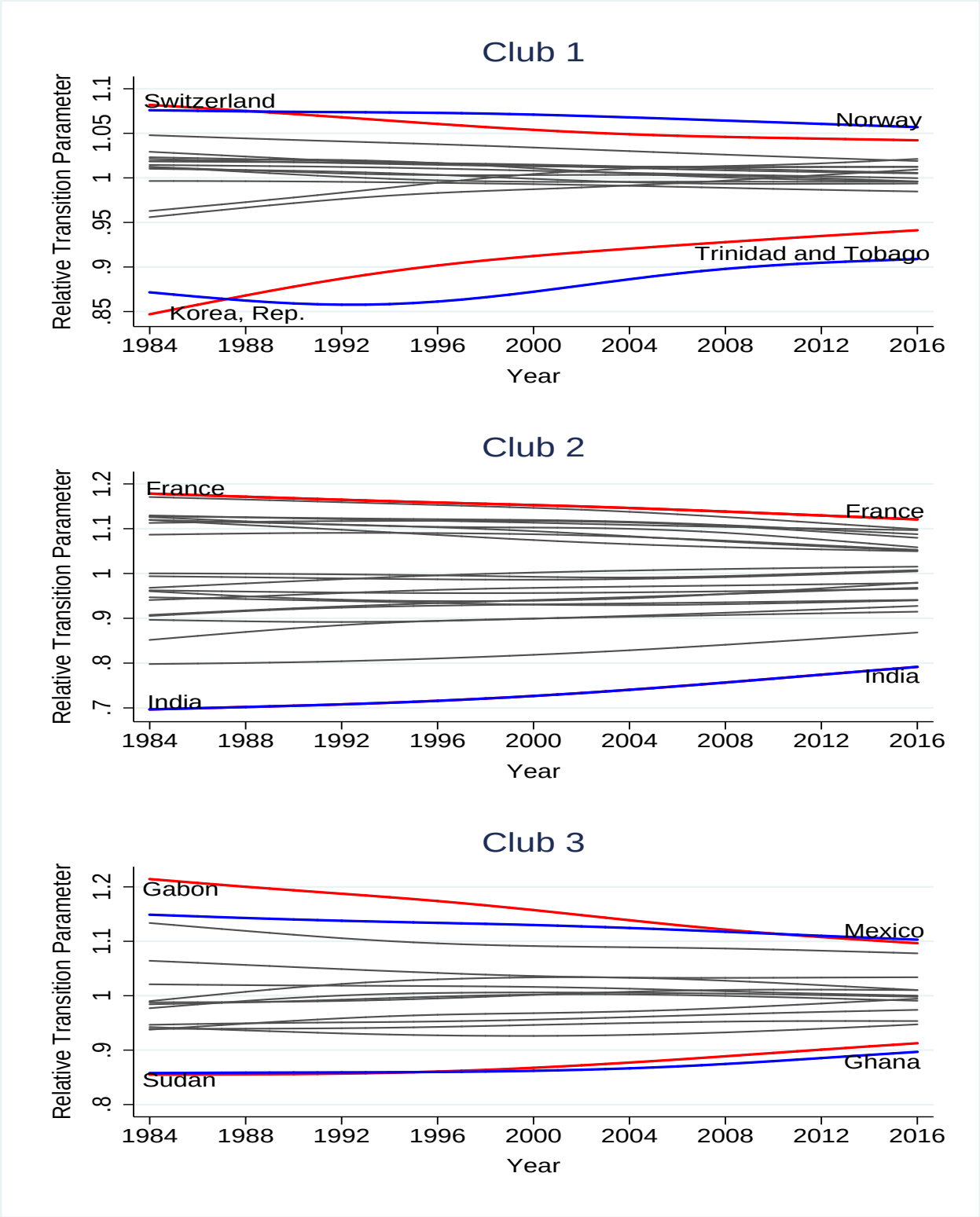

Figure 5. Relative transition curves for by convergence clubs

Table 11. Growth effect of FDI across clubs: System GMM estimates

	Private credit			Real per capita GDP		
	Full	Club 1	Club 2	Club 1	Club 2	Club 3
Initial income	-0.061***	-0.070***	-0.006	-0.118***	-0.092	-0.099**
	(0.014)	(0.024)	(0.036)	(0.022)	(0.076)	(0.038)
FDI	0.163***	0.109**	0.449***	0.087*	0.139**	0.735*
	(0.058)	(0.050)	(0.133)	(0.042)	(0.064)	(0.380)
Gov't consumption	-0.305***	-0.239*	-0.576**	-0.952***	-0.114	-0.057
	(0.101)	(0.142)	(0.195)	(0.244)	(0.174)	(0.218)
Openness	0.063***	0.074**	0.028	0.131***	0.029	-0.015
	(0.022)	(0.028)	(0.109)	(0.030)	(0.079)	(0.068)
Inflation	-0.053***	-0.058***	-0.044	-0.298***	-0.069*	-0.042
	(0.015)	(0.016)	(0.065)	(0.063)	(0.037)	(0.026)
Schooling	0.027*	0.026	0.013	0.080*	0.065	0.052
	(0.015)	(0.030)	(0.038)	(0.040)	(0.109)	(0.034)
Observations	620	510	110	170	220	150
Number of countries	62	51	11	17	22	15
Hansen test (p-value)	0.729	0.483	0.406	0.466	0.463	0.362
AR(2) test (p-value)	0.122	0.378	0.117	0.108	0.956	0.171

Notes: Each column shows the coefficient from a separate regression using 3-year average data. The estimation method is two-step system GMM with Windmeijer's (2005) finite-sample correction. All variables are cross-sectionally demeaned log values. Windmeijer (2005)-corrected cluster-robust standard errors are in parentheses. ***, **, and * indicates statistical significance at the 1% , 5%, and 10% level.

Table 12. Robustness: Growth effect of FDI across clubs, system GMM estimates

	Private credit			Real per capita GDP		
	Full	Club 1	Club 2	Club 1	Club 2	Club 3
Initial income	-0.064***	-0.063***	-0.069**	-0.082***	-0.094**	-0.093***
	(0.011)	(0.012)	(0.031)	(0.015)	(0.034)	(0.017)
FDI	0.181*	0.142*	0.643**	0.077**	0.002	0.403*
	(0.104)	(0.082)	(0.284)	(0.036)	(0.150)	(0.201)
Gov't consumption	-0.158*	-0.188**	-0.186	-0.613***	-0.059	-0.022
	(0.085)	(0.086)	(0.220)	(0.146)	(0.181)	(0.112)
Openness	0.019	0.046*	-0.086	0.096***	-0.002	-0.060
	(0.026)	(0.027)	(0.070)	(0.024)	(0.072)	(0.049)
Inflation	-0.041***	-0.037***	-0.046	-0.313***	-0.055***	-0.021
	(0.013)	(0.013)	(0.046)	(0.054)	(0.019)	(0.013)
Schooling	0.040***	0.031*	0.051	0.023	0.109	0.065**
	(0.015)	(0.016)	(0.047)	(0.033)	(0.084)	(0.026)
Observations	372	306	66	102	132	90
Number of countries	62	51	11	17	22	15
Hansen test (p-value)	0.424	0.594	0.381	0.345	0.344	0.360
AR(2) test (p-value)	0.662	0.352	0.714	0.665	0.353	0.627

Notes: Each column shows the coefficient from a separate regression using 5-year average data. The estimation method is two-step system GMM with Windmeijer's (2005) finite-sample correction. All variables are cross-sectionally demeaned log values. Windmeijer (2005)-corrected cluster-robust standard errors are in parentheses. ***, **, and * indicates statistical significance at the 1% , 5%, and 10% level.

Table 13. Growth effects of FDI: dynamic threshold regression estimates

	Full	Club 1	Club 1	Club 2	Club 2
Threshold ($\hat{\gamma}$)	92.582	92.582	92.582	10.948	8.985
	[83.748-97.492]	[83.748-97.492]	[83.748-97.492]	[10.431-17.068]	[8.985-17.068]
Impact of FDI					
$\hat{\beta}_1 FDII(FD \leq \hat{\gamma})$	0.235***	0.201***	0.261***	-0.304	-0.343
	(0.046)	(0.050)	(0.053)	(0.286)	(0.214)
$\hat{\beta}_2 FDII(FD > \hat{\gamma})$	0.033	0.029	0.039	0.640***	0.613***
	(0.031)	(0.032)	(0.032)	(0.218)	(0.171)
Impact of covariates					
Initial Income	-0.025**	-0.029*	-0.026	0.031	0.014
	(0.012)	(0.017)	(0.018)	(0.033)	(0.023)
Govt Consumption	-0.217***	-0.199***		-0.393**	
	(0.069)	(0.017)		(0.205)	
Openness	0.032**	0.048***		0.027	
	(0.015)	(0.017)		(0.043)	
Inflation	-0.035***	-0.041***		0.009	
	(0.011)	(0.011)		(0.034)	
Schooling	0.012	0.001	0.015	0.005	0.022
	(0.015)	(0.023)	(0.023)	(0.027)	(0.020)
$\hat{\delta}$	0.012***	0.011***	0.011***	0.017	0.032**
	(0.004)	(0.004)	(0.004)	(0.016)	(0.013)
Countries	62	51	51	11	11
Observations	620	510	510	110	110

Notes: Each column shows the coefficient from a separate regression using 3-year average data. Club formation is based on private credit. Standard errors are in parentheses. ***, **, and * indicates statistical significance at the 1% , 5%, and 10% level.

Table 14. Robustness: Growth effects of FDI, dynamic threshold estimates

	Full	Club 1	Club 2
Threshold ($\hat{\gamma}$)	95.617	95.617	17.756
	[54.774-96.698]	[87.600-103.077]	[10.863-31.585]
Impact of FDI			
$\hat{\beta}_1 FDII(FD \leq \hat{\gamma})$	0.218***	0.171***	0.009
	(0.044)	(0.043)	(0.423)
$\hat{\beta}_2 FDII(FD > \hat{\gamma})$	-0.041	-0.048	0.842**
	(0.034)	(0.032)	(0.345)
Impact of covariates			
Initial Income	-0.024**	-0.027**	0.053
	(0.012)	(0.015)	(0.048)
Govt consumption	-0.151**	-0.138**	-0.356
	(0.073)	(0.071)	(0.356)
Openness	0.004	0.022	0.033
	(0.017)	(0.018)	(0.067)
Inflation	-0.033***	-0.037***	0.033
	(0.010)	(0.012)	(0.044)
Schooling	0.013	0.003	0.001
	(0.015)	(0.021)	(0.041)
$\hat{\delta}$	0.005	0.005	0.013
	(0.004)	(0.004)	(0.018)
Countries	62	51	11
Observations	372	306	66

Notes: Each column shows the coefficient from a separate regression using 5-year average data. Club formation is based on private credit. Standard errors are in parentheses. ***, **, and * indicates statistical significance at the 1% , 5%, and 10% level.

Table 15. Robustness: Dynamic threshold regression estimates

	Club 1	Club 2	Club 3
Threshold ($\hat{\gamma}$)	53.956	92.582	52.956
	[43.590-108.082]	[88.056-100.472]	[8.670-56.918]
Impact of FDI			
$\hat{\beta}_1 FDII(FD \leq \hat{\gamma})$	0.494***	0.318**	0.268
	(0.159)	(0.131)	(0.193)
$\hat{\beta}_2 FDII(FD > \hat{\gamma})$	0.052**	-0.053	0.056
	(0.025)	(0.121)	(0.166)
Impact of covariates			
Initial Income	-0.064*	-0.027	-0.003
	(0.033)	(0.045)	(0.039)
Govt Consumption	-0.846***	-0.066	-0.145
	(0.128)	(0.092)	(0.182)
Openness	0.106***	0.044	0.031
	(0.030)	(0.043)	(0.026)
Inflation	-0.296***	-0.02	-0.031***
	(0.088)	(0.019)	(0.011)
Schooling	0.016	0.006	-0.009
	(0.047)	(0.078)	(0.034)
$\hat{\delta}$	0.002	0.015*	0.013
	(0.006)	(0.008)	(0.013)
Countries	17	22	15
Observations	170	220	150

Notes: Each column shows the coefficient from a separate regression using 3-year average data. Club formation is based on real per capita GDP. Standard errors are in parentheses. ***, **, and * indicates statistical significance at the 1% , 5%, and 10% level.

VITA

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