Essays in International Macroeconomics

by

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Kent Kimbrough

Dissertation submitted in partial fulfillment of the requirements for the degree of
Doctor of Philosophy in the Department of Economics
in the Graduate School of Duke University
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Abstract

This dissertation consists of two essays in international macroeconomics. In the first essay I explore the role of portfolio diversification in explaining the distribution of foreign investment across countries. I do so by adopting a portfolio allocation approach to risk, that is widely used in empirical finance, to complement more traditional analyses of foreign capital flows across countries. I capture the portfolio diversification motive by a measure of country-specific riskiness, "covariance risk", which I construct as how countries' growth rates covary with the stochastic discount factor of a representative international investor. The idea is to capture the extent to which investments in a foreign economy provide a hedge against the investor's overall risk. My key new empirical finding is a strong and significant correlation between this new measure of country riskiness and foreign investment allocations. *Less* risky countries, i.e countries whose growth rates are more highly correlated with the investor's stochastic discount factor, receive larger investment shares than *more* risky countries. I interpret this result as evidence that investors do take into account diversification opportunities not only for portfolio investment decisions but also for foreign direct investment decisions. My empirical results confirm the theoretical predictions of standard portfolio allocation models.

In the second essay I explore the business cycle regularities of low-income countries in comparison to those observed in middle- and high-income countries. The data reveals several distinguishing features of the business cycle in low-income countries

compared to the other two income groups: acyclical trade balances; highest volatility of consumption relative to output; highest volatility of debt; highest average debt-to-output ratio and lowest average savings ratio; significant negative correlation between domestic saving rates and the net foreign asset position. My main finding is that a small open economy model with both trend and transitory shocks to productivity, and varying intertemporal elasticity of substitution, motivated by subsistence consumption theories, can be used to account for the distinguishing features of the three income groups. The theoretical model shows that while both permanent shocks and transitory fluctuations around the trend are important sources of fluctuations in low-income countries, temporary shocks play a predominant role. In comparison to the other two income groups the volatility of the temporary shock for the low-income countries is more than three times higher than that for the high-income group and twice as large as that for the middle-income group. The same pattern holds for the permanent shock.

To my husband, Guus, for his love, understanding, and endless patience.

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1

Portfolio Diversification and the Cross-Sectional Distribution of Foreign Investment

1.1 Introduction

This paper contributes to the literature on the determinants of foreign investment by considering the role of portfolio diversification. Unlike the literature on portfolio investment, the literature on foreign direct investment (FDI) does not explore the portfolio selection motive behind investors' decisions. The literature on FDI looks at the cross-sectional distribution of investment as the result of investors evaluating countries on their individual merits. Real-world evidence, however, suggests that multinational corporations (MNCs) take diversification opportunities into account when making investment decisions. For example, in the last year the Wall Street Journal documented the experience of several MNCs such as HSBC, Banco Santander and Tesco PLC that benefited from regional diversification, especially in the current economic downturn.

My objective is to explore the role of diversification in the cross-sectional distribution of total foreign investment, which includes FDI as well as portfolio investment.

To do so I extend the existing analyses of the determinants of foreign investment by adopting a portfolio allocation approach to risk. I capture the portfolio diversification motive by a measure of country-specific riskiness, which I refer to as "covariance risk". I construct this measure as how countries' growth rates covary with the stochastic discount factor (SDF) of a representative international investor. The idea is to capture the extent to which investments in a foreign economy provide a hedge against the investor's overall risk.

I find evidence that investors do take into account diversification opportunities. My key new finding is that less risky countries, i.e. countries whose growth rates are more highly correlated with the investor's SDF, receive larger investment shares than more risky countries. This result has both statistical as well as strong economic significance. For example, if a country's riskiness declines from the 25^{th} percentile to the 75^{th} percentile, on average the total foreign investment per capita increases by more than 135 %.

My approach allows me to study the role of portfolio diversification in the distribution of foreign investment in general and across a large sample of countries that includes low-income countries. First, I look at total foreign investment that includes both FDI and portfolio investment. The role of diversification has been studied for portfolio investment allocations, but not for FDI allocations. It is important to explore FDI allocations because the data shows that FDI is the main component of foreign investment for the majority of countries. Portfolio investment constitutes a significant share of total foreign investment only for high-income countries, while for the majority of low- and middle-income countries FDI is more than 90 percent of total foreign investment. Second, my measure of covariance risk that captures the investors' diversification motive is available for 104 countries. In contrast, the empirical literature on portfolio investment usually uses stock market return correlations, which limits the country coverage to countries with well developed stock markets and reliable stock market data.

I study the role of portfolio diversification in the distribution of foreign investment using both a theoretical and an empirical approach. In the theoretical motivation I show that the share of investment a foreign economy receives is a decreasing function of the covariance of its returns with the returns of the investor's domestic economy. This covariance of returns captures the idea of diversification in the model. I use a standard portfolio allocation model based on Merton (1969, 1971) and incorporate elements that have been used in the literature (see for example Kraay and Ventura (2000); Kraay et al. (2005); Asiedu et al. (2009); Coeurdacier and Guibaud (2010)), but have either been studied separately or have not been thoroughly explored. This allows for a general theoretical framework of allocation of foreign investment that includes both FDI and portfolio investment.

Next, I test whether this theoretical prediction finds support in the data. In my empirical investigation I capture the portfolio diversification motive by a new measure of country-specific riskiness: "covariance risk". This measure is constructed in Burnside and Tabova (2009) as the covariance between countries' growth rates and a measure of global risk that is a proxy for the stochastic discount factor (SDF) of a representative international investor. The approach is analogous to the two-pass regression method used in empirical finance to explain cross-sectional variation in expected returns across portfolios, with country growth rates replacing portfolio returns in the regressions. The first step is to obtain country-specific exposures to global risk factors. The risk factors are: the US real GDP growth, the US real interest rate, the change in the relative prices of oil, metals, and agricultural commodities, and the US stock market excess return. The second step is to obtain the cost of risk by regressing average growth rates on the estimated exposures to the risk factors. Using this approach Burnside and Tabova (2009) construct a measure of global risk that is a proxy for the global investor's SDF. All relevant information about a country's exposure to global risk factors can be summarized in the covariance (or beta) between its growth rate and this proxy SDF. This single variable is my covariance risk measure. Countries with higher values of this measure are *less* risky because their growth rates are more highly correlated with the stochastic discount factor.

For the empirical analysis I use two measures of foreign investment: (i) the stock of FDI originating from the US; and (ii) the stock of total FDI and portfolio investment, adjusted for valuation effects (see Lane and Milesi-Ferretti, 2009).

My key empirical finding is a strong and significant correlation between my measure of country riskiness and the foreign investment allocations across countries. Riskier countries receive smaller shares of FDI originating from the US than less risky countries. Riskier countries also attract less total FDI and portfolio investment. The results show that the diversification motive, captured by countries' riskiness, has statistical as well as strong economic significance. In my analysis I control for factors that the existing literature has identified as important determinants of investment allocations, including expropriation risk (see Asiedu et al., 2009; and Blonigen, 2005 for an extensive overview of the empirical literature). The results are also robust when I use an estimation procedure that accounts for the fact that the measure of covariance risk is a generated regressor.

The results of the paper suggest that mitigation of covariance risk has the potential to make countries more attractive for foreign investment. This has important implications especially for developing countries where foreign investment finances development projects and is crucial in bridging the gap between domestic savings and investment needs.

The rest of the paper is organized as follows. Section 2 introduces the theoretical model that links foreign investment to covariance risk. Section 3 describes the data and variables used in the empirical analysis. It provides the details of how the new measure of covariance risk is constructed. Section 4 describes the empirical methodology and presents the main results and robustness checks. Section 5 outlines the policy implications and concludes.

1.2 A model of foreign investment and portfolio diversification

I use a portfolio allocation approach to model the role of portfolio diversification in the distribution of foreign investment. The model is based on Merton (1969, 1971). It relates closely to Kraay and Ventura (2000) and Kraay et al. (2005) who use portfolio selection models to examine classical questions in international economics. In the model a representative investor chooses how to distribute his/her capital stock among the domestic economy, (N-1) foreign economies, and a riskless asset. The representative investor's lifetime utility is:

$$\int_0^\infty \ln c(t) e^{-\rho t} dt \qquad \rho > 0 \tag{1.1}$$

where c is consumption and ρ is the rate of time preference ($\rho > 0$). Capital is the only factor of production and there is a single good that can be used for consumption and investment. To simplify the exposition, I assume that capital does not depreciate over time. The production function is linear in the capital stock in all economies. The stochastic rate of return for the domestic and foreign economies is:

$$\mathbf{R}\, dt \;+\; \mathbf{\Sigma}^{1/2}\, \mathbf{dz} \;-\; \mathbf{dq}$$

$$\mathbf{R} = \begin{bmatrix} R_P \\ \mathbf{R_F} \end{bmatrix} \qquad \text{is the vector of mean returns}$$

$$\mathbf{\Sigma} = \begin{bmatrix} \sigma_P^2 & \omega' \\ \omega & \Sigma_F \end{bmatrix} \qquad \text{is the covariance matrix of returns}$$

R_P is the mean return in the domestic economy, R_F is the vector of mean returns in the foreign economies, σ_P^2 is the variance of the domestic economy's returns, ω is the vector of covariances of the foreign economies' returns with the domestic economy's returns, $\mathbf{\Sigma_F}$ is the covariance matrix of the foreign economies' returns, $\mathbf{dz}$ is the vector of Wiener processes. Since contracts across borders cannot be enforced, the international investor faces the risk that the host country may either expropriate or unilaterally modify the contract governing the investment. The probability of expropriation is captured by the term dq, which is a Poisson process.[1] In this formulation the threat of expropriation is exogenous from the investor's point of view. This is analogous to the set-up in the theoretical literature on the role of expropriation where although the decision of expropriation is endogenously determined by the recipient country, it is taken as given by the international investor (Eaton and Gersovitz, 1984).[2] If expropriation occurs the entire output accrues to the host country and the representative investor does not invest in this country in the future. This assumption is standard in the literature.

Denote by k the aggregate capital stock. Let ϕ_P be the share invested in the domestic economy, $\phi_{\mathbf{F}}$: the vector of shares invested in foreign economies. Then the fraction employed in the riskless activity, ϕ_f, is:

$$\phi_f = 1 - \phi_P - \sum_{j=1}^{N-1} \phi_j$$

The investor's budget constraint can be expressed as follows:

$$dk = \Big[\{\phi'(R - r^f \iota) + r^f\}\, k - c\Big]\, dt + k\, \phi'\, \Sigma^{1/2}\, dz - k\, \phi'\, dq \tag{1.2}$$

where $\phi \equiv [\phi_P, \phi_{\mathbf{F}}]$. The budget constraint illustrates the trade-off between

[1] The Poisson process is a continuous-time process which allows discrete (i.e. discontinuous) changes in the variables.

[2] In their seminal paper, Eaton and Gersovitz (1984) the decision of expropriation is determined by the binding expropriation constraint that states that the host country's discounted income if expropriation occurs equals the host country's discounted income if no expropriation occurs.

risk and return that underlies investment decisions. To determine the optimal consumption and capital allocation rules the representative investor maximizes his/her lifetime utility subject to the budget constraint. The optimization problem is:

$$\rho J = max_{\{c,\phi\}} \Big\{ ln(c) + \frac{\partial J}{\partial k} \Big[\{\phi'(R - r^f \iota) + r^f\} \, k - c \Big] +$$

$$+ \frac{1}{2} \frac{\partial^2 J}{\partial k^2} k^2 [\phi' \, \Sigma \, \phi] + \alpha' [J(k^d) - J(k) \iota] \Big\} \tag{1.3}$$

where k^d is the capital stock in the event of expropriation, α is the vector of probabilities of expropriation. Throughout I impose the usual transversality condition and assume that the investor's holdings of capital in all economies are nonnegative.[3] In this framework closed form solutions for the portfolio allocations are obtained.[4] The optimal consumption rule is:

$$c = \rho \, k \tag{1.4}$$

The optimal investment shares are:

$$\phi_P = \sigma_P^{-2}(R_P - r^f) - \sigma_P^{-2} \phi_F' \omega \tag{1.5}$$

$$\phi_F = \Sigma_F^{-1}(R_F - r^f \iota) - \Sigma_F^{-1} \omega \phi_P - \mathbf{\Sigma_F}^{-1} [\mathbf{I}_{n-1} - \mathbf{D}(\phi_\mathbf{F})]^{-1} \alpha \tag{1.6}$$

where $D(\phi_F)$ is a diagonal matrix with the capital shares $\phi_\mathbf{F}$ on the diagonal. Equations (4),(5), and (6) show that both the consumption-capital ratio and the

[3] See Merton (1990) for proof and discussion of the role of the form of the value function for the solution of the problem.

[4] For utility functions of the form yielding constant relative risk aversion the problem can be solved explicitly.

fractions of capital employed in the foreign economies are constant. Equation (4) states that consumption depends only on the aggregate stock of capital. For the special case of logarithmic utility that I use here, the consumption decision is independent of the expected return or the variances and covariances of the economies' returns. Equations (5) and (6) state that the international investor behaves as a mean-variance investor. For example, the share of capital invested in each foreign economy equals its expected excess return relative to its variance and covariance and corrected for the risk of expropriation. For constant relative risk aversion utility the investment decision is independent of the consumption decision (Samuelson, 1969 and Merton, 1969).[5] [6]

Denote by ω_i the covariance between foreign economy i and the domestic economy, and by ϕ_i the share of investment in the foreign country i. I interpret ω_i as the measure of country i's covariance risk. Then the role of county i's covariance risk on the share of foreign investment it receives can be expressed as:

$$\frac{\partial\, \phi_i}{\partial\, \omega_i} = \frac{-\,\phi_P\,({\mathbf{\Sigma_F}}^{-1})_{ii} - \frac{\partial\,\phi_P}{\partial\,\omega_i}\,[({\mathbf{\Sigma_F}}^{-1})_i\;\;\omega]}{\alpha_{\mathbf{i}}\,(\mathbf{1}-\phi_{\mathbf{i}})^{-\mathbf{2}}\,({\mathbf{\Sigma_F}}^{-1})_{ii} + 1} \tag{1.7}$$

where $({\mathbf{\Sigma_F}}^{-1})_{ii} > 0$ is the i^{th} coefficient on the diagonal of matrix Σ_F^{-1}; $({\mathbf{\Sigma_F}}^{-1})_i$ is the i^{th} row of matrix Σ_F^{-1}. In the model this derivative captures the role of portfolio diversification in the distribution of foreign investment. The first term of the numerator, i.e. $\phi_P\,({\mathbf{\Sigma_F}}^{-1})_{ii}$, and the denominator are positive, so the sign of the derivative depends on the sensitivity of the share of investment in the domestic economy to its covariance with the foreign economies. To evaluate the sign of the derivative I use two approaches. First, I follow the literature on "home bias" that

[5] I consider only interior optimal solutions. If the problem is formulated in the more general Khun-Tucker form the equalities of (4),(5), and (6) will be replaced with inequalities.

[6] Merton (1990) shows that the sample paths of consumption and capital are identical to those generated in the complete markets case.

allows me to analytically sign the derivative. Second, I use numerical evaluation. In both cases I find that the derivative is strictly negative: the share of foreign investment is decreasing in its covariance with the domestic economy.

First, equation (7) shows that the share of foreign investment is decreasing in the covariance, $\frac{\partial \phi_i}{\partial \omega_i} < 0$, if the share of investment in the domestic economy is not sensitive to its covariance with the foreign economies, i.e. when $\frac{\partial \phi_P}{\partial \omega_i} = 0$. The literature on "home bias" provides a reason why this might be the case. I follow this literature and introduce an investment constraint that states that the share of capital invested in the domestic economy must exceed a certain threshold; this restriction is binding (see for example Coeurdacier and Guibaud, 2010):

$$\phi_P = \underline{\phi}_P > \phi_P^*$$

where ϕ_P^* is the optimal share for the unconstrained problem and $\underline{\phi}_P$ is fixed. This type of restriction reflects both regulatory constraints faced by investors as well as risk management practices of MNCs or institutional investors. Since the constraint is binding, the investor is forced to invest more in its economy than it is optimal under the unconstraint problem. The portfolio constraint forces a "home bias": a widely documented and studied phenomenon in the literature on international portfolio allocations. The constraint limits the investor's portfolio choice by fixing the share of investment in the domestic economy. Therefore:

$$\frac{\partial \phi_i}{\partial \omega_i} = \frac{-\,\phi_P\,(\mathbf{\Sigma_F}^{-1})_{ii}}{\alpha_{\mathbf{i}}\,(\mathbf{1}-\phi_{\mathbf{i}})^{-\mathbf{2}}\,(\mathbf{\Sigma_F}^{-1})_{ii}+1} < 0$$

Second, using a numerical evaluation, I show that even if the share invested in the domestic economy, ϕ_P, is sensitive to changes in the covariance, ω_i, the share invested in the foreign economy i is strictly decreasing in ω_i. I evaluate the derivative numerically for the case of a single foreign economy i. Figures 1.1 and 1.2 show the simulated fractions of capital for a range of plausible values for the covariance and for different magnitudes of the risk of expropriation. I set the range of values for ω to correspond to the range of values observed in the data for the covariance of the US per capita GDP growth rate with the GDP growth rates of 106 countries. The time period is 1971-2007. I set σ_P^2 equal to the variance of the US per capita GDP growth, which is 0.036; and $(\Sigma_F)_{ii}$ equal to the median variance of per capita GDP growth for the sample of countries, which is 0.15. The plot does not change much for a broader range of values for $(\Sigma_F)_{ii}$ and σ_P^2. Finally, I set $R_P - r^f$ and $R_i - r^f$ to correspond to the average growth rates in the US, $\bar{g}^P$, and the median of the average growth rates of countries in the sample, $\bar{g}^i$, such that $\bar{g}^P - \bar{g}^i = -(R_P - R_i)$. The plots show the negative relation between the fraction of investment employed in the foreign economy, ϕ_i, and its covariance with the domestic economy ω_i:

$$\frac{\partial \phi_i}{\partial \omega_i} < 0$$

Although the focus of this paper is on the role of covariance risk, I also take into account the risk of expropriation. The role of expropriation risk on foreign country i's investment allocation, ϕ_i, can be expressed as follows:

$$\frac{\partial \omega_i}{\partial \alpha_i} = - \frac{(\mathbf{\Sigma_F}^{-1})_{ii}\,(1-\phi_i)^{-1}}{\alpha_\mathbf{i}\,(\mathbf{1}-\phi_\mathbf{i})^{-\mathbf{2}}\,(\mathbf{\Sigma_F}^{-1})_{ii} + 1} < 0$$

To summarize, the model shows that the covariance of returns does play a role in the decision making process of a representative international investor. The more negatively correlated the return of a foreign economy is with the investor's home economy, the larger the share of capital that the investor is willing to allocate to that economy. This relationship captures the role of diversification in the foreign investment allocations across countries. In what follows, I develop a general empirical

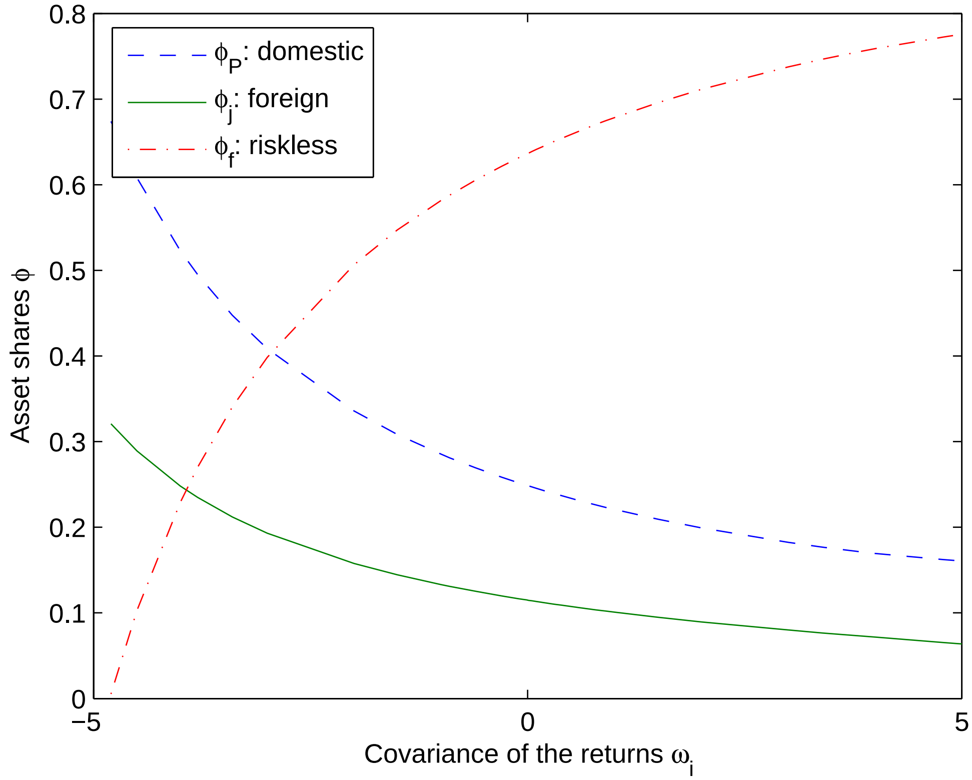

FIGURE 1.1: Investment shares for a range of values for ω_i, $\alpha_i = 0.1$

specification to study whether this relationship holds in the data.

1.3 Measures of covariance risk and foreign investment

Before proceeding with the empirical analysis, in this Section I first describe the main variables for the analysis: foreign investment and my measure of covariance risk that captures the diversification motive behind investors' allocation decisions.

1.3.1 Covariance risk

In my empirical investigation I capture the portfolio diversification motive by a new measure of country-specific riskiness, which I refer to as covariance risk. This new measure is constructed in Burnside and Tabova (2009) as the covariance between countries' growth rates and a measure of global risk that is a proxy for the stochastic

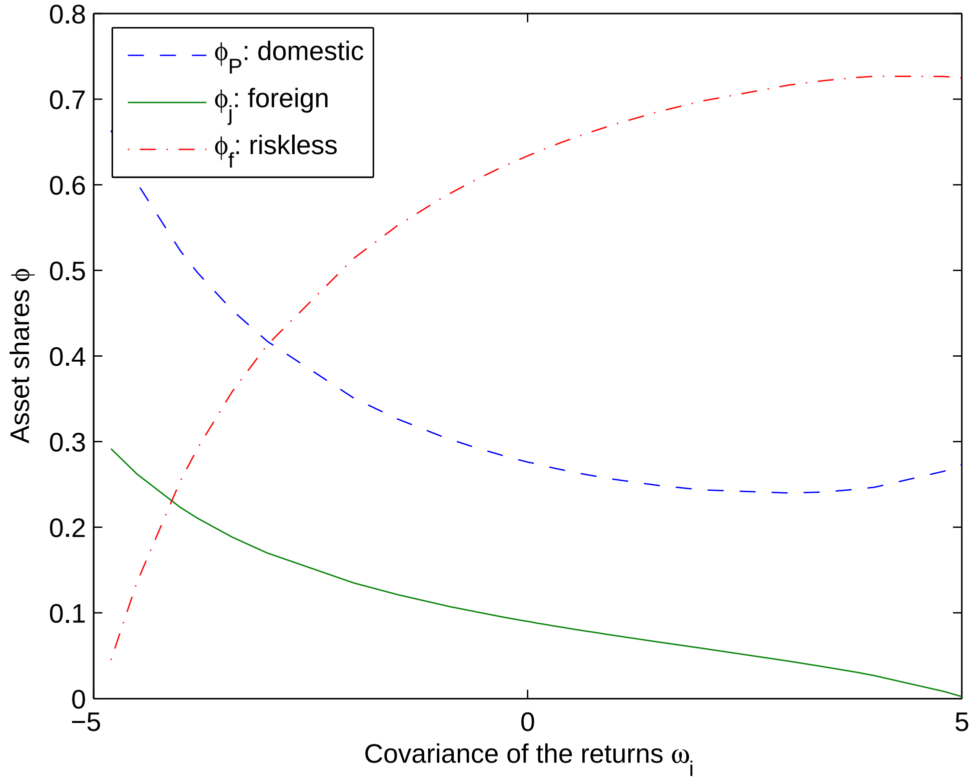

FIGURE 1.2: Investment shares for a range of values for ω_i, $\alpha_i = 0.5$

discount factor (SDF) of a representative international investor. The approach is analogous to the two-pass regression method used in empirical finance to explain cross-sectional variation in expected returns across portfolios, with country growth rates replacing portfolio returns in the regressions. Ideally one would assess whether risk explains differences in rates of return across countries by gathering data on rates of return to investment, and estimating an explicit model of the international investor's stochastic discount factor. Unfortunately this approach is fraught with difficulty.[7]

[7] One might, for example, assume a Cobb-Douglas production technology and measure the marginal product of capital in each country and at each point in time, using assumptions about model parameters and data on output and capital stocks. It is not trivial to measure capital stocks. See, for example, Klenow and Rodriguez-Clare's (1997) analysis of the neoclassical growth model, in which they measure capital stocks by accumulating investment data in the Penn World Tables. However, if rates of return are inclusive of adjustment costs, further assumptions about functional

The first step is to obtain country-specific exposures to global risk factors. The risk factors are: the US real GDP growth, the US real interest rate, the change in the relative prices of oil, metals, and agricultural commodities, and the US stock market excess return. This involves time series regression of each country's real growth rate, g_{it}, on a vector of six risk factors, $\mathbf{f}_t$:

$$g_{it} = a_i + \mathbf{f}_t'\beta_i + \epsilon_{it}, \quad t = 1, \ldots, T, \text{ for each } i = 1, \ldots, n.$$

the time period is 1971-2007 for a total of 104 countries. The choice of the factors is motivated by the notion that to some extent they reflect global demand conditions, global financial conditions, and terms of trade shocks that might be considered important to the small economies in our sample. The betas, β_i, measure countries' exposure to the risk factors. The bar graphs in Figure 1.3 show the frequency distribution across countries of the betas by factor. There are two important findings from this estimation. First, the results show a considerable spread among the betas, β_i, across countries. Second, between roughly 15 and 30 percent of the estimated betas are individually statistically significant at the 5 percent level. The black dots in the bar graphs indicate the number of betas within each cell that are statistically significant at the 5 percent level.

The second step is to obtain the cost of risk by regressing average growth rates on the estimated exposures to the risk factors using a single cross-sectional regression of average growth rates g_i on the estimated β_i from the time series regression:

$$g_i = \lambda_0 + \hat{\beta}_i'\lambda + u_i, \qquad i = 1, \ldots, n$$

where $\hat{\beta}_i$ is the OLS estimate of β_i obtained in the time series regression, and u_i is an error term. The parameter λ measures the cost in percentage points of

forms need to be made. Measuring returns to investment in human capital would be even more difficult.

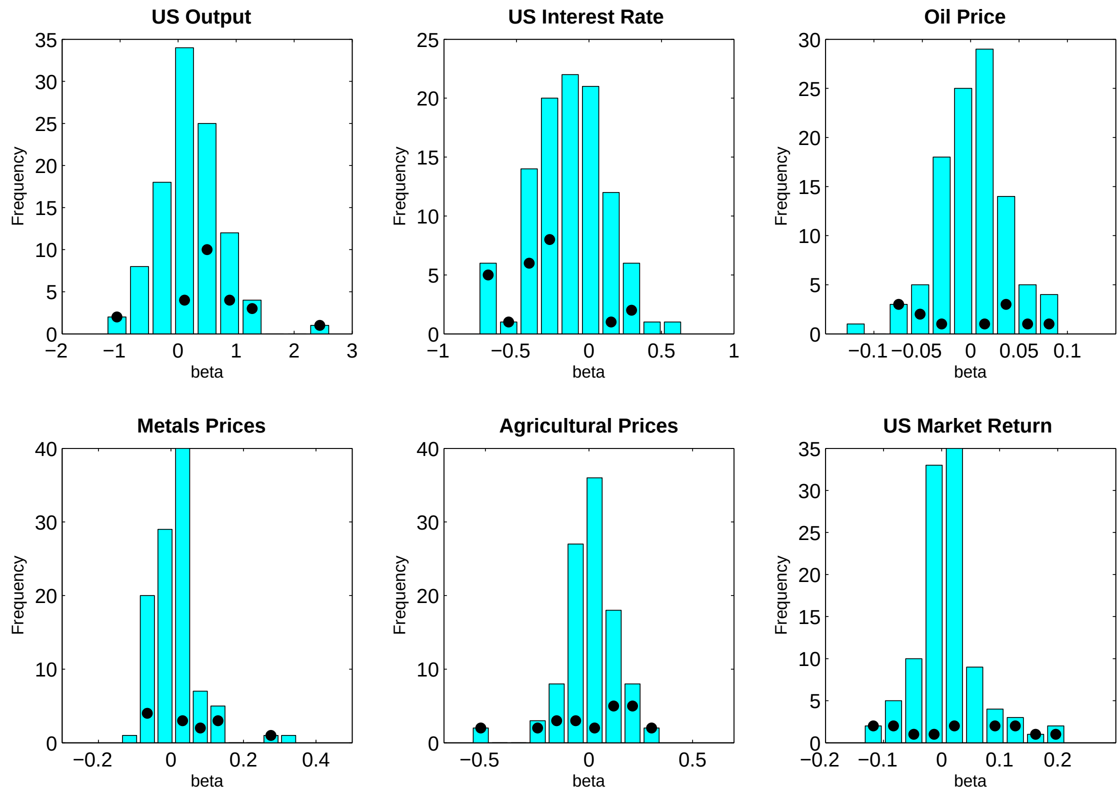

FIGURE 1.3: Estimates of the betas, β_i, for the vector of risk factors

growth, of different exposures to risk. Using this approach Burnside and Tabova (2009) construct a measure of global risk that is a proxy for the global investor's SDF $\hat{m}_t$:

$$\hat{m}_t = \left(\mathbf{f}_t - \overline{\mathbf{f}}\right)' \hat{\boldsymbol{\Sigma}}_{\mathbf{f}}^{-1} \hat{\lambda}$$

All relevant information about a country's exposure to global risk factors can be summarized in the covariance (or beta) between its growth rate and this proxy SDF. This single variable is my "covariance risk" measure, β_{mi}:

$$\beta_{mi} = \frac{cov(g_i, \hat{m})}{var(\hat{m})} = \frac{cov(g_i, \mathbf{f}')\Sigma_f^{-1}\lambda}{\lambda'\Sigma_f^{-1}\lambda} = \frac{\beta_i \lambda}{\lambda'\Sigma_f^{-1}\lambda}$$

Countries with higher values of this measure are *less* risky because their growth rates are more highly correlated with the stochastic discount factor. The degree of a country's riskiness, β_{mi}, depends on the sign and magnitude of its exposure to the specific risk factors, β_i. For example, countries with more negative exposures to US interest rates and more positive exposures to changes in oil and metals prices are riskier. Risk exposure is highly correlated with initial income: the highest-income countries tend to have roughly zero β_{mi}, while lower income countries tend to have negative β_{mi}.

It is useful to establish the explicit link between the empirical measure of covariance risk and the measure ω_i that I used in the theoretical model. Recall that the empirical measure of covariance risk is: $\beta_{mi} = \text{cov}(g_i, \hat{m}) / var(\hat{m})$. Since the global stochastic discount factor $\hat{m}$ is the same for all countries, $\text{cov}(g_i, \hat{m})$ identifies the country-specific riskiness. Replacing g_i with R_i does not change the sign of the covariance: the sign of $\text{cov}(R_i, \hat{m})$ will be the same as the sign of $\text{cov}(g_i, \hat{m})$.[8] The direct link between the empirical and theoretical measure of covariance risk can be expressed as:

$$\beta_{mi} \propto - \omega_i$$

Therefore, for the data to confirm the theoretical predictions of the role of portfolio diversification, in the empirical investigation we would expect to find a positive correlation between β_{mi} and the foreign investment allocations across countries:

$$\frac{\partial \phi_i}{\partial \omega_i} \propto - \frac{\partial \phi_i}{\partial \beta_{mi}} < 0$$

[8] The covariances are time-series statistics. In standard stochastic growth models rates of return and growth rates of GDP are highly correlated in the time series dimension because changes in technology and labor inputs (as opposed to the slow-moving changes in capital inputs) drive the comovements. Improvements in technology and increases in labor inputs due to other shocks increase growth and the marginal product of capital, and, hence, the rate of return to investments in capital. Hence, at a minimum, the sign of $\text{cov}(R_i, \hat{m})$ will be the same as the sign of $\text{cov}(g_i, \hat{m})$.

1.3.2 *Foreign investment*

In the empirical analysis I use two measures of foreign investment: (i) the stock of FDI originating from the US; and (ii) the stock of total FDI and portfolio investment. I do not consider the debt-creating component of capital flows for two main reasons. First, the focus of the paper is on pure investment motives that are not reflected in debt flows. Second, official concessional lending, which is not determined by investment objectives, is the main component of the debt stock for the majority of low-income countries in the sample.

The source of data for FDI originating from the US is the International Economics Accounts reported by the Bureau of Economic Analysis. The data is available for 93 countries. For total FDI and portfolio investment I use a new database constructed by Lane and Milesi-Ferretti (2006) where the stock measures are adjusted for valuation effects, such as exchange rate changes, variations in the price of capital goods and changes in the values of stock market indices. The stock data also takes into account unrecorded capital flight and debt reductions that are not captured in "crude" cumulative current account data. The data is available for 145 countries.

Given that most of the variation in the data is across countries, it is appropriate to consider average stock of foreign investment and estimate a single cross-sectional regression. Since capital liberalization plays an important role for the dynamics of foreign inflows, I use average stock for each recipient country for the period 1995-2007.[9] Before the early 1990s capital movements were still restricted in many economies, and foreign investment was, therefore, less sensitive to the economic and institutional environment (see Lane and Milesi-Ferretti (2003, 2005, 2006), Harms and Lutz (2006)).

[9] It is customary in the empirical literature on FDI to smooth out cyclical fluctuations by averaging the dependent and independent variables. See Harms and Lutz (2006), Asiedu et al. (2009) among others.

1.4 Empirical analysis

The theoretical model in Section 2 shows that portfolio diversification does play a role in the decision making process of a representative international investor. The more negatively correlated the return of a foreign economy is with the investor's home economy, the larger the share of capital that the investor is willing to allocate to this foreign economy. Now I develop a general empirical specification to study whether this relationship holds in the data. I first use data on FDI originating from the US. Next, I capture the role of portfolio diversification on total foreign investment by using data on recipient countries' total stock of FDI and portfolio investment. In the empirical analysis I use my measure of covariance risk to capture the portfolio diversification motive behind investors' decisions.

1.4.1 Portfolio diversification and FDI originating from the US

Figure 1.4 shows that the covariance risk measure, β_{mi}, is positively related with the US FDI allocations across countries. This positive relation can be interpreted as initial evidence that the theoretical predictions find support in the data. Note that by construction countries

with higher values of β_{mi} are *less* risky since their growth rates are more positively correlated with the investor's stochastic discount factor. In Figure 1.4 countries are sorted by their stock of FDI scaled either by the total stock of US FDI across all recipient countries or by population and are then grouped into quartiles. The vertical axis shows the average β_{mi}. The horizontal axis of each graph shows the average stock of FDI expressed either as a share of the total US FDI across all countries or in per capita terms.

In addition, I use simple bivariate cross-sectional regressions to show that the correlation between covariance risk and foreign investment is strongly statistically

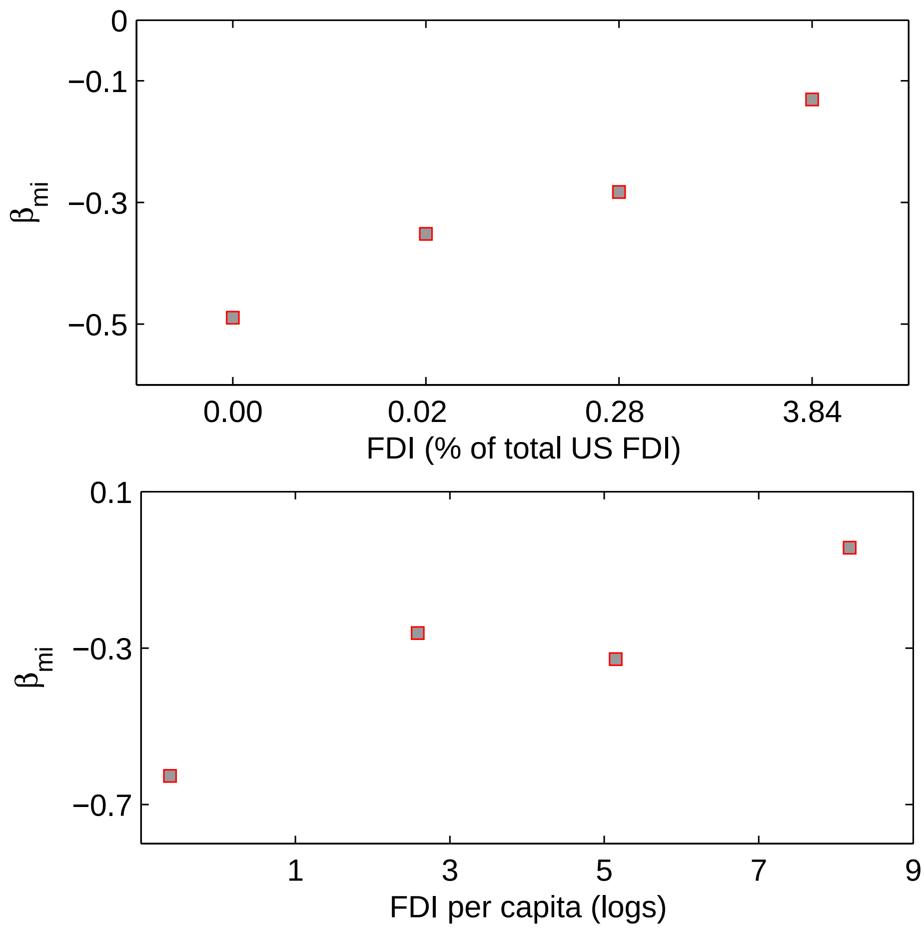

FIGURE 1.4: FDI^{US} versus covariance risk β_{mi}

significant (see Table 1.1). The results hold for either measure of FDI. The full sample includes all 92 countries for which I have constructed the new measure of country-specific riskiness (covariance risk) and for which data is available of FDI originating from the US. For a robustness check I also exclude the largest recipients of FDI^{US}. These are Canada (CAN), the Netherlands (NLD), and Great Britain (GBR) in the case of FDI_i/FDI^{US}; and the financial centers Bahamas (BHS), Bermuda (BMU), Luxembourg (LUX), and Panama (PAN) for the case of FDI per capita.

Table 1.1: FDI originating from the US and covariance risk (1995-2007)

Dependent variable	Constant	Covariance risk	R^2
FDI per capita: FDI_i/Pop_i (log)			
Full sample	4.54***	2.06***	0.127
	(0.40)	(0.54)	
Excluding LUX, BMU, BHS, PAN	4.21***	1.77***	0.102
	(0.40)	(0.58)	
FDI as a share of total: FDI_i/FDI^{US} (log)			
Full sample	-2.55***	1.71***	0.085
	(0.41)	(0.62)	
Excluding CAN, NLD, GBR	-2.77***	1.60***	0.081
	(0.41)	(0.61)	

Notes: Heteroscedasticity-consistent standard errors in parentheses.

Holding companies and redirection of FDI

US parent companies funnel a share of their direct investments abroad through holding company affiliates.[10] Data from BEA shows that in 2007 30 percent of the US direct investment position abroad is accounted for by holding companies, which may have invested the funds in other countries. To take this into account, I check if the positive relationship between the stock of FDI and β_{mi} is preserved for bilateral FDI originating from the countries with the largest share in $\mathrm{FDI}^{\mathrm{US}}$ and the largest share of holding companies recipients of $\mathrm{FDI}^{\mathrm{US}}$: the Netherlands (NL) and the United Kingdom (UK). In 2007 the Netherlands held 14 percent of total $\mathrm{FDI}^{\mathrm{US}}$ and 68 percent was accounted for by holding companies; the UK held 13 percent of total $\mathrm{FDI}^{\mathrm{US}}$ and 22 percent was accounted for by holding companies (source: BEA 2008, 2009). The source of data on bilateral FDI stock originating from the Netherlands

[10] A holding company is a company whose primary activity is holding the securities or financial assets of other companies.

and the UK is OECD International Direct Investment Statistics, the sample period and methodology are identical to the ones used above for the FDI originating from the US. When I regress the FDI per capita (in logs) on β_{mi}, I obtain the following estimates:

$$\text{FDI}_i^{\text{UK}} = \underset{(0.36)}{4.24} + \underset{(0.65)}{1.58}\beta_{mi} \qquad R^2 = 0.07 \tag{1.8}$$

$$\text{FDI}_i^{\text{NL}} = \underset{(0.32)}{2.78} + \underset{(0.54)}{1.22}\beta_{mi} \qquad R^2 = 0.05 \tag{1.9}$$

where heteroskedasticity-consistent standard errors are in parentheses. The results show that for both the Netherlands and the United Kingdom the positive relationship between β_{mi} and FDI allocations is preserved. Therefore, even though the final destination of the funds channeled through holding companies is unknown, there is evidence that the countries with the largest share of holding companies in the FDI portfolio of the US follow the logic of portfolio diversification.

Controlling for traditional determinants of FDI

Next, I show that my key empirical finding on the role of portfolio diversification, captured by my covariance risk measure, is preserved if I control for country-specific characteristics drawn from the empirical literature on the determinants of FDI.[11] In the cross sectional regression I include an expropriation risk rating to capture the risk that host countries might either expropriate the foreign investment or unilaterally modify the contract governing the investment. This is a more traditional measure of risk that has been used in recent empirical studies. The source of data is the

[11] Hausmann and Fernandez-Arias (2001); Asiedu et al. (2002, 2009) among others.

International Country Risk Guide database.[12] A high score implies less risk.[13] The rating is available for 80 of the 93 countries in my sample. I also include GDP growth rates to capture growth opportunities in the host country; the level of GDP as a measure of market size; (Exports + Imports)/GDP as a measure of trade openness; the number of phones per 1000 people as a measure of infrastructure availability and the level of development.[14] The data source for these variables is the World Development Indicators (2009). To be consistent with the dependent variable, I average the control variables over the same period. An additional control variable is the distance between the capitals of the originating country and the host country as a proxy for the relative magnitude of transaction costs. Transaction costs of control and potential problems stemming from cultural differences are expected to increase with distance.[15] The descriptive statistics are reported in Appendix A.

Since most of the variation in the data is across countries, reflecting conditions that change slowly, I use cross-sectional regressions. All variables are averages for the period 1995-2007. The model I estimate is:

$$Y_i = \gamma_0 + \gamma_1 \beta_{mi} + \mathbf{Z_i} \mathbf{\Gamma_2} + \epsilon_i \tag{1.10}$$

where β_{mi} is the measure of covariance risk, $\mathbf{Z}$ is the vector of control variables described above, and $\mathbf{\Gamma_2}$ is the coefficient vector associated with the control variables. I first estimate the model using the shares of countries' FDI, FDI_i/FDI^{US}, as the

[12] See International country risk guide (2007).

[13] The consensus in the empirical literature is that expropriation risk has a negative effect on FDI (see Loree and Guisinger (1995), Asiedu et al. (2009) among others).

[14] Some empirical studies use GDP per capita as a proxy for development. Since the number of phones is highly correlated with GDP per capita (correlation coefficient 0.91) and can be used as a proxy for availability of infrastructure in the host country (see Asiedu et al., 2009), it is an appropriate control variable for this study.

[15] Distance is usually featured in gravity models that are widely used in empirical international economics, most commonly in trade studies. A number of studies, however, have shown that the gravity model also has explanatory power when applied to FDI. Brainard (1993, 1997) provides a theoretical model for gravity-like forces for FDI analyses.

dependent variable Y_i. This estimation provides a direct link to the predictions of the theoretical model where the representative investor solves for optimal investment shares across the foreign economies. I also estimate the model using per capita FDI originating from the US, as the dependent variable.

First, I estimate the model by OLS. The sample includes 78 countries due to data availability of the expropriation risk rating. Columns 1 and 3 in Table 1.2 presents the results of this estimation. The coefficient on covariance risk, β_{mi}, is positive and significant at the 3 percent level. This means that less risky countries from the international investor's perspective, i.e. those with higher values for β_{mi}, receive on average a larger share of the total stock of FDI. Less risky countries have also a higher level of FDI per capita.

The results show that the diversification motive, captured by my covariance risk measure, has statistical as well as strong economic significance. The 25^{th} percentile value for the β_{mi} in the sample is -0.69, while the 75^{th} is 0.02. The point estimates for the coefficient associated with β_{mi} suggest that the cross-sectional regression predicts that if a country's riskiness declines from the 25th percentile to the 75th percentile, on average per capita FDI from the US increases by more than 183 percent. The magnitude is similar for the case when the share of FDI is the dependent variable. This empirical result confirms the theoretical prediction: the stock of FDI in a foreign economy, measured either in per capita terms or as a share of total FDI across all countries, is a decreasing function of the covariance of its return with the return of the investor's home economy.

I now turn my attention to the other explanatory variables. Table 1.2 shows that consistent with Asiedu et al. (2009) the coefficient on the expropriation risk variable is positive and significant for all specifications. Recall from the data description section that higher values of the expropriation risk rating imply *less* risk. I find that openness to trade, infrastructure availability, and the size of the domestic market, measured by either level of GDP or population, have a positive and significant effect on FDI. As expected, oil producers attract on average a larger share of FDI; while distance is negatively and significantly correlated with FDI.

Because β_{mi} is a generated regressor, it may be the case that the estimate of γ_1 is biased towards zero because of measurement error.[16] This would only reinforce my finding of a positive relationship between FDI holdings and the measure of covariance risk β_{mi}. A related concern in the case of generated regressors is that OLS standard errors understate the true standard errors. To address this issue I use maximum likelihood estimation (MLE). My approach follows Kim (1995) who derives a maximum likelihood estimator that takes into account the measurement error of the generated regressor. Kim (1995) develops the correction for the two-pass estimation methodology of expected returns, but the correction can easily be applied for more general problems. The Appendix to this chapter contains a detailed description of the MLE methodology. The correction provides a robustness check for the validity of the uncorrected OLS estimates and standard errors.

Columns 2 and 4 in Table 1.2 present the MLE results along with the OLS coefficients for comparison. Consistent with the theory, the results show that the OLS estimation results in an underestimation of the coefficient associated with β_{mi} (the variable measured with error). The correction does not change the main findings and serves as a robustness check for the link between FDI and covariance risk.

[16] This is in the case of classical attenuation bias (see Wooldridge 2001), assuming that measurement errors are orthogonal to the other variables of interest.

Table 1.2: Impact of covariance risk on the stock of FDI originating from the US after controlling for country-specific factors

	Dependent var.: FDI_i/FDI^{US} (log)		Dependent var.: FDI per capita (log)	
	OLS	MLE	OLS	MLE
Covariance risk (β_{mi})	0.978**	1.533**	0.836**	1.217**
	(0.472)	(0.722)	(0.419)	(0.583)
GDP growth	-0.279**	-0.270**	-0.287**	-0.278**
	(0.137)	(0.123)	(0.131)	(0.110)
ln(GDP)	1.326***	1.351***	0.536***	0.544***
	(0.152)	(0.141)	(0.138)	(0.124)
Trade/GDP	0.014***	0.015***	0.015***	0.016***
	(0.003)	(0.004)	(0.003)	(0.003)
$ln(1 + Phones)$	1.337***	1.263***	0.759**	0.702***
	(0.237)	(0.206)	(0.306)	(0.245)
$ln(Distance)$	-0.915***	-0.904***	-1.039***	-1.025***
	(0.317)	(0.345)	(0.365)	(0.318)
Expropriation risk	2.318*	2.349**	2.144*	2.130**
	(1.231)	(1.178)	(1.193)	(1.039)
Oil exporter dummy	0.918	1.149*	0.606	0.755
	(0.729)	(0.602)	(0.688)	(0.525)
Constant	-24.756***	-25.021***	-6.505	-6.564
	(3.977)	(4.355)	(4.071)	(4.115)
obs	78	78	78	78
R^2	0.776	0.767	0.800	0.795

Notes: Heteroscedasticity-consistent standard errors in parentheses. *(10%), **(5%), ***(1%). Countries with higher values of β_{mi} are *less* risky. Similarly, higher values of the expropriation risk variable imply *lower* expropriation risk.

1.4.2 *Portfolio diversification and total stock of foreign investment*

In this section I explore the role of portfolio diversification using (i) the entire stock of FDI in the recipient countries, and (ii) the stock of total foreign investment that includes FDI as well as portfolio investment (PO). The data is adjusted for valuation effects (see Lane and Milesi-Ferretti, 2009).

The scatter plot of FDI versus total foreign investment shows that FDI is the main component of total foreign investment for the majority of countries. Portfolio investment constitutes a significant share of total foreign investment only for the high-income countries (see Figure 1.5). The summary statistics in Table 1.3 confirm this fact. Therefore, in the cross-section the majority of variation in foreign investment is explained by the variation in FDI rather than portfolio investment.

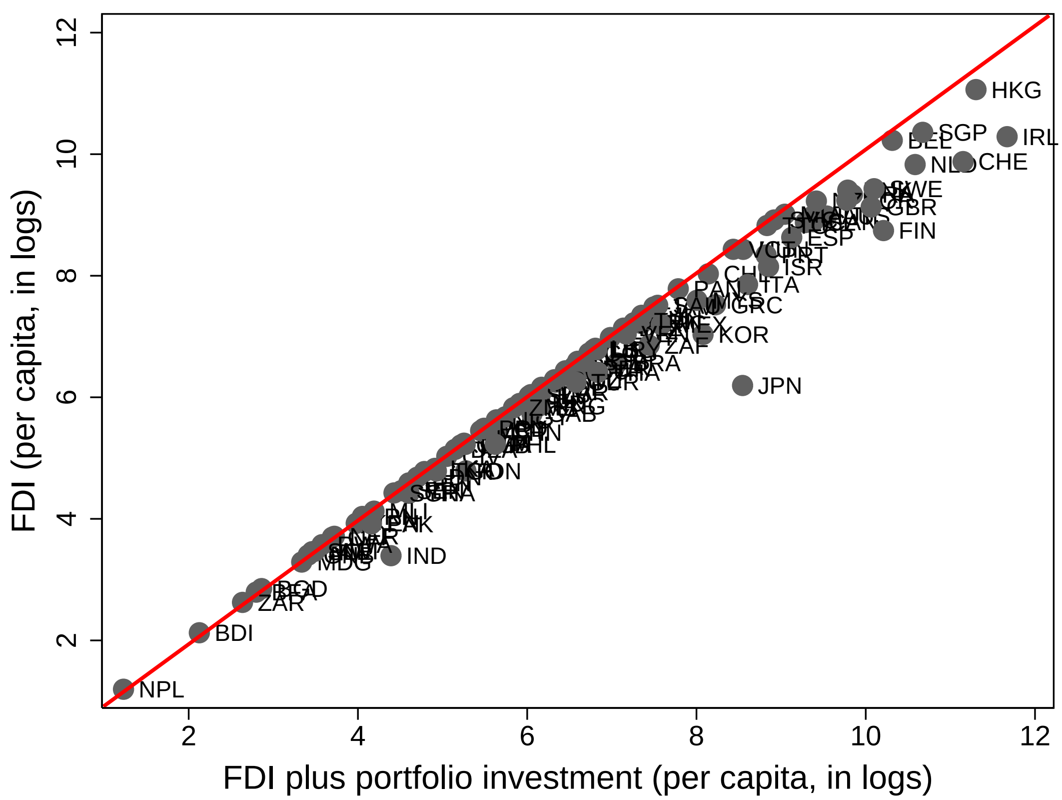

Figure 1.5: FDI versus FDI plus portfolio investment (average 1995-2007)

Using this new database I again find evidence that the international investors take into account diversification opportunities in their allocation decisions. Figure 1.6 shows that foreign investment across countries is positively associated with my covariance risk measure, β_{mi}. By construction countries with higher values β_{mi} are *less* risky since their growth rates are more positively correlated with the investor's stochastic discount factor. In the Figure countries are sorted either by the stock of FDI per capita or by the total stock of foreign investment and are then grouped into quartiles. The vertical axis shows the average β_{mi}, while the horizontal axis of each graph shows either the average per capita FDI or the average per capita total foreign investment.

In addition, in Table 1.4 I use simple bivariate cross-sectional regressions to show that the correlation between covariance risk and foreign investment is statistically significant. The relation between β_{mi} and foreign investment is preserved if the sample includes only low- and middle-income countries. The results also confirm the evidence from Figure 1.5 that for low- and middle-income countries the majority of foreign investment is explained by FDI rather than portfolio investment.

Table 1.3: Share of FDI in total foreign investment: FDI/(FDI+PO) (mean 1995-2007)

	Obs.	Mean	Median	St.Dev.
Low-income countries	34	0.933	0.989	0.131
Middle-income countries	29	0.864	0.920	0.141
High-income countries	30	0.633	0.611	0.236

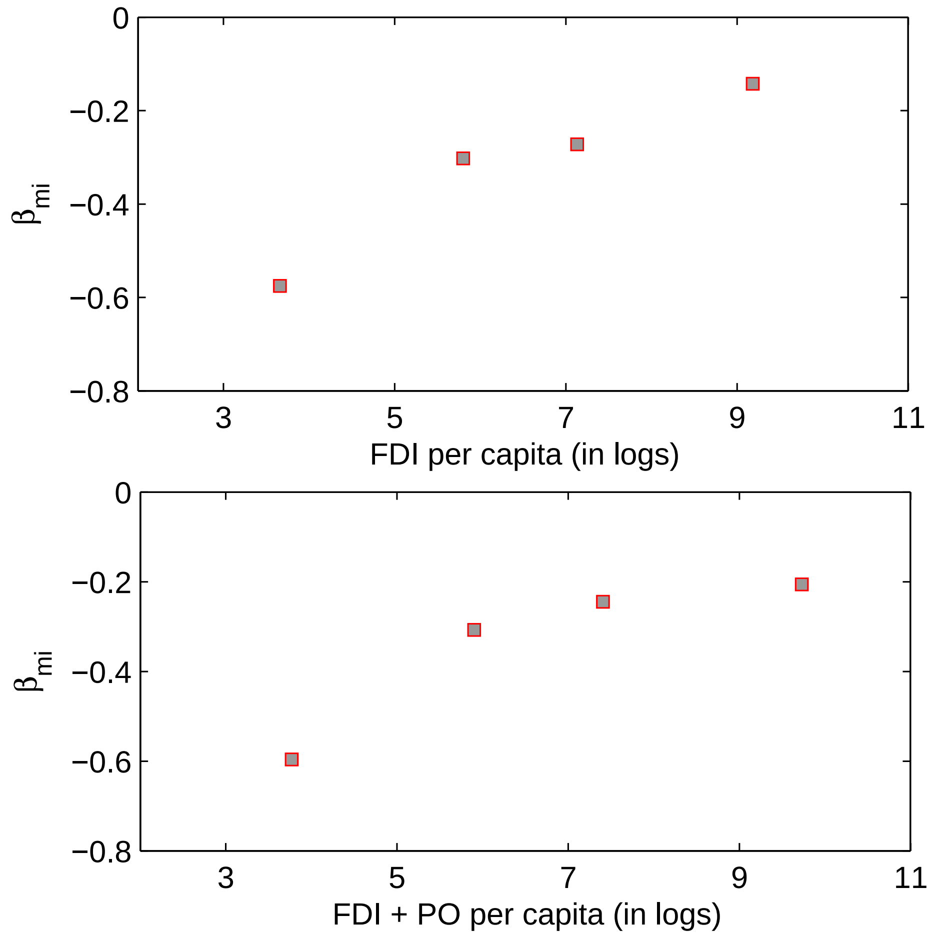

FIGURE 1.6: Foreign investment versus covariance risk β_{mi}

Controlling for traditional determinants of foreign investment

Next, I show that my key empirical finding on the role of portfolio diversification, captured by my covariance risk measure, is preserved if I control for the country-specific characteristics described in the previous Section. For the regressions where the dependent variable is total foreign investment I include dummies for the high-income countries in the sample to account for the fact that portfolio investment constitutes a significant share of foreign investment only for these countries.

The results show a strong and significant relation between my measure of covariance risk and foreign investment, measured either by per capita FDI or per capita

Table 1.4: Impact of covariance risk on the total stock of foreign investment

	Right-hand side variables			
	Constant	Covariance risk β_{mi}	R^2	obs
A. Full sample				
Regressions with FDI	6.96	1.16	0.104	90
	(0.26)	(0.30)		
Regressions with FDI + PO	7.24	1.24	0.100	90
	(0.28)	(0.32)		
B. Low and middle-income countries				
Regressions with FDI	5.67	0.61	0.069	61
	(0.22)	(0.23)		
Regressions with FDI + PO	5.81	0.63	0.071	61
	(0.23)	(0.23)		

Notes. Dependent variable: in log per capita. *(10%), **(5%), ***(1%).
Heteroscedasticity-consistent standard errors in parentheses.

total foreign investment that includes portfolio investment. Countries that are perceived as more risky, i.e. countries with lower values of the covariance risk measure, receive lower levels of per capita foreign investment.

This relationship is not only statistically significant, but has economic significance as well. The 25^{th} percentile value for the β_{mi} in the sample is -0.69, while the 75^{th} percentile value is 0.02. The point estimates for the coefficient associated with β_{mi} suggest that the cross-sectional regression predicts that if a country's covariance risk declines from the 25th percentile to the 75th percentile, on average total foreign investment per capita increases by more than 165 percent. The estimated increase for FDI per capita is 135 percent. Also, the role of the control variables is preserved: the coefficient on the expropriation risk variable is positive and significant for all specifications, openness to trade, infrastructure availability, and the size of the domestic market, have a positive and significant effect on total foreign investment. The results do not change if the size of the domestic market is measured by the countries' population instead of the level of their GDP.

1.5 Concluding remarks

In this paper I explore the role of diversification in the cross-sectional distribution of total foreign investment, which includes FDI as well as portfolio investment. To do so I extend the existing analyses of the determinants of foreign investment by adopting a portfolio allocation approach to risk. I capture the portfolio diversification motive by a measure of country-specific riskiness, which I refer to as "covariance risk". I construct this measure as how countries' growth rates covary with the stochastic discount factor of a representative international investor. I develop a general empirical specification that highlights the role of diversification but allows for host country specific characteristics to also influence portfolio allocations. My key new result is that the diversification motive, captured by my covariance risk measure, has statistical as well as strong economic significance. Therefore, I find empirical evidence that international investors take into account diversification opportunities in their investment allocation decisions, which confirms the predictions of standard portfolio allocation models.

The results of this paper suggest that mitigation of covariance risk has the potential to make countries more attractive to foreign investment. This has important implications especially for developing countries where foreign investment finances development projects and is crucial in bridging the gap between domestic savings and investment needs. The degree of country riskiness, captured by the covariance risk measure, depends on the sign and magnitude of the country-specific exposures to common shocks. For example, countries with more negative exposures to US interest rates and more positive exposures to changes in commodity prices are riskier from the perspective of the international investor. Therefore, policy measures that target

Table 1.5: Impact of covariance risk on the total stock of foreign investment after controlling for country-specific factors

	FDI		FDI + Portfolio investment	
	OLS	MLE	OLS	MLE
Covariance risk (β_{mi})	0.420**	0.461**	0.431**	0.489**
	(0.203)	(0.230)	(0.204)	(0.248)
GDP growth	-0.087	-0.067	-0.062	-0.062
	(0.047)	(0.051)	(0.047)	(0.057)
ln(GDP)	-0.067	-0.079	0.023	0.023
	(0.067)	(0.065)	(0.068)	(0.072)
Trade/GDP	0.010***	0.009***	0.009***	0.009***
	(0.003)	(0.002)	(0.003)	(0.002)
$ln(1 + Phones)$	1.211***	1.234***	0.947***	0.938***
	(0.157)	(0.122)	(0.184)	(0.160)
Expropriation risk	1.726***	1.540***	1.469***	1.460***
	(0.599)	(0.577)	(0.577)	(0.651)
Oil exporter dummy	0.985***	0.972***	0.826***	0.851***
	(0.307)	(0.277)	(0.275)	(0.307)
High-income country dummy			1.242***	1.248***
			(0.297)	(0.338)
Constant	1.254	1.941	0.140	0.182
	(1.984)	(1.888)	(1.901)	(2.106)
obs	80	80	80	80
R^2	0.882	0.893	0.890	0.889

Notes. Dependent variable: in log per capita; *(10%), **(5%), ***(1%).
Heteroscedasticity-consistent standard errors in parentheses.

economic diversification, or external debt reduction in the case of countries with high exposure to the US interest rate might lead in the longer run to a lower degree of riskiness. Although oil rich countries attract a large share of foreign investment, this investment is concentrated in the oil sector. Diversification might help attract foreign investment in the non-oil sectors that can have a more direct positive impact on economic development.

Related to these policy implications, an important direction of future research is exploring the time variation of the measure of riskiness. This will allow a comparison of riskiness not only across countries, but across time periods as well and can help identify economic developments or policies that might have contributed to a reduction or increase in riskiness over time. Another avenue for research is the role of holding companies. The data shows that 30 percent of the US direct investment position abroad is accounted for by holding companies, which may have invested the funds in other countries. Therefore, an important task of future research will be to allocate investment in holding companies to their ultimate destination.

2

Business cycle fluctuations in low-income countries

2.1 Introduction

The study of emerging-market business cycles and how they compare to those of high-income countries has received much attention in the literature (see Fernàndez-Villaverde et al., 2010, Aguiar and Gopinath, 2007, Neumeyer and Perri, 2005, and Uribe and Yue, 2006, among others), but less work has focused on the least-developed countries. I this paper I present a comprehensive set of empirical statistics for a group of 33 low-income countries and compares them to the business cycle regularities of the middle- and high-income groups. I show that a small open economy model with both trend and transitory shocks to productivity, and varying intertemporal elasticity of substitution (IES), motivated by subsistence consumption theories, can be used to account for the distinguishing features of the three income groups.

The data reveals several distinguishing features of the business cycle in low-income countries. First, low-income countries exhibit acyclical trade balances, while for the majority of countries in the other two income groups the trade balance is highly countercyclical. Second, low-income countries show the highest volatility of consumption relative to output. Third, in terms of debt dynamics, the low-income group shows the highest volatility of debt and the highest average debt-to-output ratio. Fourth, a distinguishing feature that has not been documented before is the relationship between domestic saving and foreign debt. While there is heterogeneity within income groups, the data at lower frequencies reveals a significant negative correlation between domestic saving rates and the net foreign asset position for the "median" low-income country. This correlation weakens as income levels increase.

After documenting the empirical facts I replicate the key business cycle differences among the three income groups using a single theoretical framework. The model is a single good, single asset small open economy model with transitory and trend shocks to productivity, and preferences featuring subsistence consumption. The model is successful in matching the distinguishing characteristics of the "median" country in each group. The results show that for the low-income countries the volatility of the temporary shock is more than three times higher than that for the high-income group and twice as high as that for the middle-income group. The same pattern holds for the permanent shock: low-income countries' volatility is significantly higher than that of the other income groups. In terms of the shocks' relative variance, for the low-income countries the variance of the temporary shocks is significantly higher than the variance of the trend shocks. I show that varying intertemporal elasticity of substitution (IES), motivated by subsistence consumption theories, plays an important role in explaining the data.

The model I present is successful in replicating the empirical regularities of the business cycle in low-income countries, for which there is limited literature. Therefore, it can be used as a benchmark for studying the impact of changes in the external environment as well as internal macroeconomic developments in these countries. In addition, the model is successful in accounting for the differences between low-income countries and the middle- and high-income groups.

This paper relates to three separate strands of the literature. First, there is a vast literature that studies business cycles in emerging and developed countries, and some more recent literature that focuses on business cycle characteristics that distinguish emerging markets from developed economies. Aguiar and Gopinath (2007) contribute the differences between the business cycle regularities in emerging markets and developed economies to the predominance of shocks to trend growth relative to transitory shocks, while Boz et al. (2008) show that emerging markets differ in the degree of uncertainty agents face when formulating expectations. Both papers use Mexico and Canada to represent emerging and developed countries respectively. Neumeyer and Perry (2005) emphasize the role of interest rate shocks in emerging markets. More recently, Fernndez-Villaverde et al. (2010) show that the higher time-varying volatility of the real interest rate faced by emerging markets in comparison with developed countries, is an important source of differences in the business cycle fluctuations in these countries.

Second, the paper relates to the much more limited literature on business cycles in the least developed countries. Kose and Riezman (2001) are the first to examine macroeconomic fluctuations in African countries using a stochastic, dynamic equilibrium model of a small open economy calibrated to represent a "typical" African country. Most recently Arellano et al. (2009) examine the effects of aid and its volatility in the context of a small open economy model calibrated to Cote d'Ivoire's macroeconomic characteristics. The current study differs from the existing literature in that I document and compare a larger set of empirical facts for three income groups: 33 low-income countries, 30 middle-income countries and 30 high-income countries, and study their distinguishing features using a single theoretical framework.

Third, this paper relates to the literature on saving behavior and debt dynamics. A small number of empirical papers has investigated whether foreign resource inflows affect domestic savings (Chenery and Stout (1966); Fry (1978, 1980); Giovannini (1985); Gupta (1987); Schmidt-Hebbel, Webb and Corsetti (1992). The empirical results are inconclusive: the estimates of the effect of foreign inflows on domestic saving vary with the empirical methods and model specifications, and with the samples used in the different studies. A separate line of empirical research focuses on the impact of foreign aid in particular on domestic saving (Griffin (1970); Boone (1994); World Bank (1994); Elbadawi and Mwega (2000)). While the majority of these studies find that spikes in foreign aid lead to a decline in domestic saving rates, the negative relationship between aid flows and saving rates could reflect reverse causality since aid is directed towards countries in distress, one symptom of which is low saving (see Loayza et. al. (2000)). However, no theoretical studies have focused on the effects of foreign capital inflows on domestic savings. The only exception is Verdier (2007) that shows that in the long run average saving rates positively affect debt accumulation in middle- and high-income countries. My paper differs from the above studies in that I document time series correlations of saving and aggregate foreign debt for a number of low-, middle-, and high-income countries and use a standard model to account for the observed differences among the income groups.

The paper is organized as follows. Section 2 presents the stylized facts for different country income groups. Section 3 outlines the theoretical model. Section 4 presents the results, and Section 5 concludes.

2.2 Empirical regularities

This section presents key aspects of the business cycle with emphasis on the distinction between low-income countries on the one hand and middle- and high-income countries on the other.

2.2.1 Country coverage and data

The entire sample consists of 93 countries and is divided into a high-income group with 30 countries, middle-income group with 30 countries and a low-income group with 33 countries. Countries are divided into these income groups according to their 2007 gross national income (GNI) per capita. Consistent with the World Bank definition, a low-income country is one with GNI per capita of \$935 or less; middle-income: between \$936 and \$11,455; and high-income: \$11,456 or more.[1] A complete list of the countries in the sample grouped by income is given in the Appendix to this chapter. While for the majority of countries data on GDP, consumption, investment, and net exports is available for the entire period 1970-2004, debt and saving rate data series are much shorter for a number of countries in the sample. The countries in the sample are those with at least 15 years of continuous observations for all data series for which statistics are calculated[2].

National accounts variables are annual series in per capita terms in constant US dollars. The source is the World Development Indications. The data for output is GDP, for consumption: total consumption expenditure, for investment: gross capital formation. Trade balance corresponds to net exports.

For data on debt stocks I use a new database constructed by Lane and Milesi-Ferretti (2006) where the stock measures are adjusted for valuation effects, such as exchange rate changes, variations in the price of capital goods and changes in the values of stock market indices. While data on flows is widely available: current account data across countries and time, only a few countries publish reliable estimates of accumulated stocks. Lane and Milesi-Ferretti (2006) construct foreign assets and liabilities for a total of 145 developed, emerging, and developing countries for the

[1] Source: World Bank, June 2008.

[2] Results obtained using data for the period 1990-2004 for all countries are not materially different. Results do not differ if I use data series denominated in constant local currency units.

period 1970-2004 using data on current account balances. My measure of debt corresponds to net foreign asset position. The Appendix to this chapter outlines in detail the data construction process. The stock data also takes into account unrecorded capital flight and debt reductions that are not captured in "crude" cumulative current account data.[3]

The data on saving rates comes from the World Development Indications and is defined as gross national saving:

$$s_t = GNI_t + NCT_t - C_t^h - G_t$$

where GNI is gross national income, NCT: net current transfers from abroad, C_t^h: consumption by households and non-profit organizations, G: general government consumption. This definition of saving takes into account debt payments, aid transfers and remittances that are an important source of foreign flows in particular for low-income countries and is therefore the most appropriate definition to use in this study compared to alternative definitions of saving such as gross domestic saving.[4]

2.2.2 Summary statistics

I focus on statistics at lower frequency generated by linearly detrending the raw data mainly because they reveal empirical regularities that have not been identified in the literature, namely the association of the domestic saving rates with foreign capital accumulation. Linear detrending does not alter the qualitative differences among income groups regarding relative volatility of macroeconomic variables and cyclicality

[3] Earlier attempts to construct debt stock series include Sinn (1990) with focus on ownership breakdown (private, public, banks); data is available for 145 countries for 1970-1987; Rider (1996): industrial countries only for 1984-93; IMF: international investment positions for most industrial and only a few developing countries, most series start in early 1980's.

[4] Gross domestic saving: $s^d = GDP - C^h - G$

of the trade balance generated at higher business cycle frequencies. Unfiltered data is used for the average saving and debt ratios, and first differenced data is used for the growth rates. For all other statistics data are first logged (except for the saving rate, debt, and trade balance) and filtered with the HP filter with parameter 11000 to mimic linear detrending. I use an HP filter to mimic linear detrending because the theoretical model I use to explain the data features a stochastic trend. Table 2.1 reports key moments of the business cycle as medians over the three income groups.

I focus on the characteristics of the "median country" in each income group. The Appendix to this chapter contains a breakdown for each country in the low-income group. Several distinguishing features of the business cycle in low-income countries is evident. First, low-income countries exhibit acyclical trade balances. Second, in terms of debt dynamics, the low-income group shows the highest volatility of debt and the highest average debt-to-output ratio. Third, a distinguishing feature that has not been documented before is the large negative correlation of saving and debt ratios. The median correlation for the low-income group is -0.35 with 30 percent of the countries in the group with correlation of 0.50 or above. This correlation weakens as income increases and for the high-income group the median is -0.06 with more than half of the countries in the sample with positive or insignificantly negative correlation. Filtered output has roughly the same autocorrelation in all three income groups. The first difference of unfiltered log output shows slightly weaker autocorrelation for the low-income group compared to the other two income groups. The low frequency filtering preserves the pattern for middle- and high-income countries that has been documented at quarterly frequency: middle-income countries have on average large negative correlation of net exports and output while developed economies show weaker countercyclical trade balances; and the relative volatility of consumption is higher for the group of middle-income countries (see Aguiar and Gopinath (2007)).

Table 2.1: Moments for low-, middle- and high-income groups (medians)

	Low-income	Middle-income	High-income
$\rho(\frac{d}{y}, \frac{s}{y})$	-0.35	-0.20	-0.06
	(0.11)	(0.09)	(0.11)
$\rho(\frac{tb}{y}, y)$	-0.03	-0.38	-0.22
	(0.10)	(0.13)	(0.12)
$\sigma(y)$	0.062	0.0672	0.0312
	(0.01)	(0.01)	(0.005)
$\sigma(c)/\sigma(y)$	1.16	1.11	1.02
	(0.16)	(0.12)	(0.12)
$\sigma(i)/\sigma(y)$	3.69	3.51	3.47
	(0.56)	(0.41)	(0.39)
$\sigma(\frac{d}{y})$	0.179	0.115	0.087
	(0.034)	(0.022)	(0.014)
$\rho(y)$	0.78	0.84	0.80
	(0.03)	(0.04)	(0.05)
$\rho(y, i)$	0.58	0.78	0.82
	(0.07)	(0.07)	(0.07)
$\rho(y, c)$	0.67	0.86	0.81
	(0.07)	(0.05)	(0.06)
mean(s/y)	0.11	0.19	0.22
	(0.01)	(0.01)	(0.01)
mean(d/y)	0.63	0.37	0.12
	(0.05)	(0.03)	(0.02)
$\rho(\Delta y)$	0.13	0.34	0.31
	(0.10)	(0.09)	(0.11)

Notes: This table lists median values of the moments for the group of low-income (33), middle-income (30), and high-income (30) countries. The values for each country in the low-income group are given in Appendix. The median of the GMM estimated standard errors are reported in parentheses. Data filtering is described in the text.

2.3 Theoretical model

In this Section I explore whether we can account for the distinguishing features of the business cycle in the three income groups using a single theoretical framework. The model is a single good, single asset small open economy model with transitory and trend shocks to productivity, and preferences featuring subsistence consumption.

2.3.1 Production technology and financial markets

The production part of the model follows that of Aguiar and Gopinath (2006). Technology is characterized by a Cobb-Douglas production function that uses capital K_t and labor L_t as inputs.

$$Y_t = e^{a_t} K_t^{\alpha} (\Gamma_t L_t)^{1-\alpha}$$

The capital share of output is α. The productivity processes a_t and Γ_t are characterized by different stochastic processes. The shock to the level of productivity a_t follows an AR(1) process:

$$a_t = \rho_a a_{t-1} + \epsilon_t^a \qquad \epsilon_t^a \sim N(0, \sigma_a)$$

The variable Γ_t is the cumulative product of shocks to the growth of productivity (trend shocks) g_t:

$$\Gamma_t = e^{g_t} \Gamma_{t-1}$$

$$g_t = (1 - \rho_g)\mu_g + \rho_g g_{t-1} + \epsilon_t^g \qquad \epsilon_t^g \sim N(0, \sigma_g)$$

where μ_g is productivity's long-run mean growth rate.

Capital depreciates at the rate δ, and changes to the capital stock entail a quadratic adjustment cost $\frac{\phi}{2}(K_{t+1}/K_t - e^{\mu_g})^2 K_t$. The economy's resource constraint is:

$$C_t + K_{t+1} = Y_t + (1 - \delta)K_t - \frac{\phi}{2}(K_{t+1}/K_t - e^{\mu_g})^2 K_t - (1 + r_t)D_t + D_{t+1}$$

The financial market structure consists of a one-period risk-free bonds denoted D_t. The total debt repayment due at period t is $(1+r_t)D_t$ and the level of new debt issued at period t is D_{t+1}. The price debt is sensitive to the level of outstanding debt (Schmitt-Grohe and Uribe, 2003):

$$1 + r_t = 1 + r^* + \psi(e^{\tilde{D}_{t+1}/\Gamma_t L_{t+1} - \overline{d}} - 1)$$

where $\overline{d}$ is steady state level of normalized debt, r^* is the world interest rate. The parameter ψ governs the elasticity of the interest rate to changes in indebtedness. $\tilde{D}$ denotes the aggregate level of debt in the economy which the optimizing agent takes as exogenous. In equilibrium $\tilde{D} = D$.

Given that a realization of g_t permanently influences Γ_t, output is non-stationary with a stochastic trend. I solve the detrended problem where for any variable X_t its detrended version is x_t: $x_t = \frac{X_t}{\Gamma_{t-1} L_t}$.

2.3.2 Varying IES: motivation

Let preferences be characterized by an utility function that features subsistence consumption (Christiano (1989), Rebelo (1992)):

$$u_t = \frac{(C_t - C^*)^{1-\gamma} - 1}{1-\gamma}$$

where C^* is the level of subsistence consumption. The introduction of subsistence consumption in the household preferences is mainly motivated by the goal to account for the differences in the savings rate among the income groups. The intuition is that poor households are not able to save because their income is sufficient to meet only basic consumptions needs, but if income increases households may start saving out of their income once these needs are met. In this theoretical setting subsistence consumption is the mechanism through which saving rates might increase with income and therefore such preferences are consistent with the empirical evidence that the savings rate is lower in poor countries than in more developed countries. When consumption C_t is close to its subsistence level, C^*, the marginal utility of consumption reaches infinity which discourages saving.

The modification of standard CRRA preferences with subsistence consumption implies that the intertemporal elasticity of substitution (IES) is no longer constant, but is $(1-C^*/C_t)(1/\gamma)$.[5] For high-income countries where current consumption level is substantially higher than the level of subsistence consumption $IES \to \frac{1}{\gamma}$, while for low-income countries $IES \to 0$ as consumption is close to its subsistence level.

2.3.3 Varying IES: empirical evidence

The consequence of using preferences with subsistence consumption is that subsistence affects the intertemporal elasticity of substitution of consumption and therefore aggregate savings. I now use consumption data to find what the implied IES ($I\tilde{E}S$) are for the different income groups:

$$I\tilde{E}S_i = (1 - c^*/c_i)(1/\gamma)$$

where c^* is subsistence consumption per capita, c_i is the median for the respective income group of average consumption per capita in constant USD, and i denotes income group. I measure the subsistence level of consumption c^* as the median of average consumption per capita for the group of Sub-Saharan countries in my sample. This seems reasonable since this group represents the poorest of the low-income countries. I find $c^* = 286$ in constant USD which is consistent with values used in the literature[6]. Table 2.2 shows the implied elasticities for different values of

[5] In the absence of subsistence consumption the intertemporal elasticity of substitution (IES) is constant: $1/\gamma$.

[6] Ben-David (1998) computes a subsistence level of consumption per capita of $300 in 1980 dollars as the least cost requirement for sustaining an individuals minimum dietary needs. Kraay and

the risk aversion parameter γ that are standard in the literature.

Table 2.2: Implied IES

		Implied IES		
Income group	c_i (per capita USD)	$\gamma = 1$	$\gamma = 1.5$	$\gamma = 2$
Low	310	0.08	0.05	0.04
Middle	1,822	0.84	0.56	0.42
High	13,189	0.98	0.65	0.49

The result shows that countries exhibit quite different IES and therefore emphasize the need for theoretical modelling that delivers distinct values for IES for the different income groups. The implied values for the intertemporal elasticity of substitution are consistent with the theory: IES for the low-income group is close to 0, while as income level increases IES gets closer to $1/\gamma$.

What truly matters in my case is how far current consumption C_t is from its subsistence level C^*. The question is how to account for this difference among the income groups while using a single theoretical model to match the differences in observed characteristics where the subsistence consumption level C^* is a constant that cannot differ across the income groups. I use an alternative that is equivalent in meaning but more practical in this case: I solve the model using $C^* = 0$, i.e I assume a CRRA utility function, but allow γ to vary across the income groups. This specification conforms with what the data shows us for the implied IES among the income groups. For large values of γ the IES declines the exact same way it does when current consumption approaches its subsistence level.

Raddatz (2000) use consumption per capita for Democratic Republic of Congo of just under \$300. For a detailed overview of conceptualization and measurement of subsistence, see Sharif (1986).

2.4 Results

I solve the detrended model numerically by log-linear approximation to the policy functions. I study three parameterizations of the model: low-income, middle-income, and high-income, estimated using data from these income groups[7].

For the model moments to be directly comparable to the data moments, I need to map the theoretical moments of the unfiltered detrended variables expressed as deviation from steady state to the moments of the HP-filtered non-detrended variables. The particular solution method I use allows us to analytically derive the moments of desired variables. The Appendix to this chapter outlines the analytical solution for HP-filtered model moments of interest. I follow Burnside (1999) to obtain autocovariances of HP-filtered data from the regular autocovariances. I follow McElroy (2008) to calculate HP-filter coefficients.

I are not only interested in the low-income countries' regularities, but also in the moments that best account for the differences among the income groups. Therefore, before proceeding with the model estimation it is informative to see to what extent these moments are sensitive to some of the paraments I plan to estimate. Varying elasticity of intertemporal substitution among the three income groups is the feature in the model that makes it possible to generate the different savings ratios observed in the data for these income groups. This is consistent with subsistence consumption theories where the effective elasticity of intertemporal substitution (the inverse of γ) is low for the low-income countries. Figure 2.1 and 2.2 show the sensitivity of the trade balance cyclicality and the correlation of domestic saving and foreign debt to

[7] Linear approximation has been used in the literature that studies the business cycle in emerging and developed economies in a unified framework: Aguiar and Gopinath (2005, 2007), Boz et. al (2008), Neumeyer and Perry (2005) all use linearization around steady state to solve the small open economy model with different parameterizations for emerging and developed economies. Log-linear approximation has also been used for the study of business cycles in low-income countries: see for example Kose and Riezman (2001).

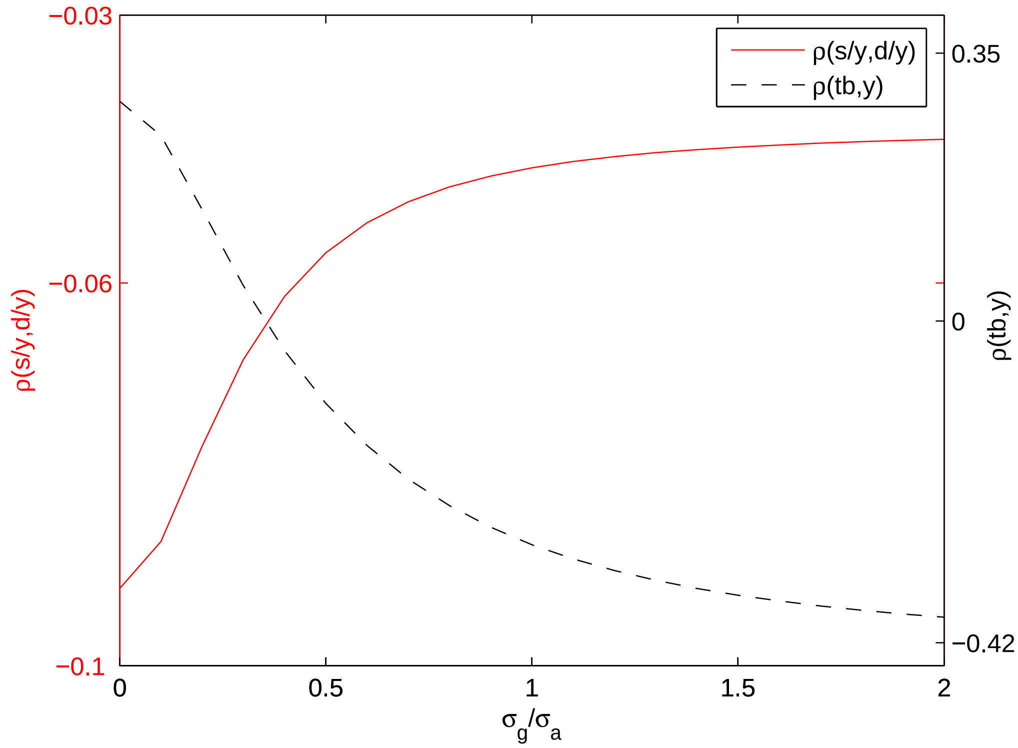

FIGURE 2.1: Sensitivity of $\rho(\frac{s}{y}, \frac{d}{y})$ and $\rho(tb, y)$ to σ_g/σ_a

the relative variances of the shocks and the risk aversion parameter[8]. It is evident that while shocks are important in generating the range of values observed in the data for the trade balance cyclicality, they are not crucial for the correlation of the saving and debt ratios. Varying the risk aversion parameter γ over a range of values common in the literature can generate the entire spectrum of $\rho(\frac{s}{y}, \frac{d}{y})$ observed in the data.

The following parameters are kept constant across the different parameterizations: the time preference rate β is set to 0.96, the depreciation rate δ is set to 0.07, the capital share α is set to 0.32, which are standard values used in real business cycle studies; and the productivity's long-run mean growth rate μ_g is set to 1.0075 following Gomme and Rupert (2007), which is also consistent with the values used

[8] The plots are generated using baseline calibration from Aguiar and Gopinath (2007)

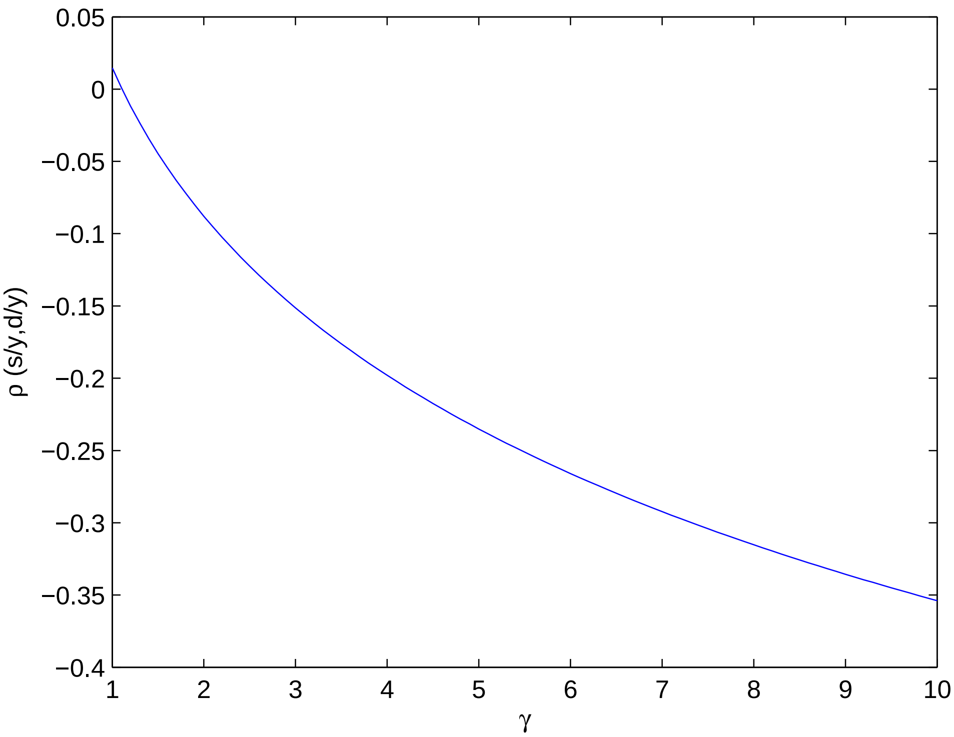

FIGURE 2.2: Sensitivity of $\rho(\frac{s}{y}, \frac{d}{y})$ to γ

in the literature that studies business cycles in developed and emerging economies. The rest of the parameters are chosen to match observations in the data for the three income groups. The value for the steady-state normalized debt $\bar{d}$ is set to match the group specific average debt-to-output ratio d/y. The risk aversion γ is set to match the group specific average saving-to-output ratio s/y. The varying values of γ for the different income groups was motivated earlier by subsistence consumption theories. The resulting values of γ are consistent with the implied IES values reported earlier. Therefore, a sensible alternative will be to use data to obtain the IES and γ for the three income groups. The remaining 6 parameters are chosen to match 6 moments simultaneously in the stochastic model. These parameters are: persistence and variance of the shocks σ_g, σ_a, ρ_g, ρ_a; coefficient on interest rate premium ψ, capital adjustment cost ϕ. The moments that I match are: 1) correlation of saving-to-output and debt-to-output ratio $\rho(\frac{d}{y}, \frac{s}{y})$, 2) correlation of trade balance and output $\rho(\frac{tb}{y}, y)$, 3) standard deviation of output $\sigma(y)$, 4) standard deviation of consumption $\sigma(c)$, 5) standard deviation of investment $\sigma(i)$, 6) standard deviation of debt-to-output ratio $\sigma(\frac{d}{y})$. The parameters are estimated by minimizing the squared difference between the model and empirical moments.

2.4.1 Parameter estimates

Table 2.3 shows all model parameters. In terms of volatility of the temporary shock I estimate $\sigma_a = 0.016$ for the low-income country group, which is more than three times larger than that for the high-income group and twice as large as that for the middle-income group. I observe the same pattern for the permanent shock: the low-income group volatility, $\sigma_g = 0.01$, is significantly larger than that of the other income groups. In terms of the shocks' relative variance, I observe that for the low-income country the variance of the temporary shock is significantly larger than the variance of the trend shock. This is consistent with existing empirical studies that argue that low-income countries are most vulnerable to transitory shocks.

For the middle-income group I find that the volatility of the two shocks do not differ much: $\sigma_g = 0.0061\%$ and $\sigma_a = 0.0071\%$. This finding differs from Aguiar and Gopinath (2007), but is consistent with Neumeyer and Perry (2005), and Boz et. al. (2008). While in Aguiar and Gopinath (2006) the predominance of shocks to trend growth relative to transitory shocks is crucial for generating the strong counter-cyclicality of the trade balance and the relative variance of consumption for middle-income countries, Neumeyer and Perry (2005) show that a framework with shocks to the country specific interest rate premium but no distinction between growth and transitory shock is consistent with the observed empirical facts for emerging markets. In my case the same result is achieved by relaxing the assumption used in previous papers that the coefficient on the interest rate premium ψ is fixed among the different income groups. This setting also helps generate $\sigma_c/\sigma_y > 1$. The estimated $\sigma_g/\sigma_a = 0.74$ for the middle-income group is consistent with Boz et al. (2008): for emerging countries (proxied by data for Mexico) they find $\sigma_g/\sigma_a = 0.78$. And finally, relaxing the assumption of fixed ψ is important for matching the variance of the debt-to-output ratio. The related studies so far do not look at this particular empirical moment or any other moment that involves d/y and therefore the interest rate premium specification (governed by the parameter ψ) is only used to induce stationarity in the small open economy model. The only exception is Garcia-Cicco et al (2009).

The resulting IES for the different groups is consistent with the implied values shown in the previous section. Low-income countries' IES is closest to 0 (0.08), while for the high-income group the IES is close to 1. The value for the high-income countries is consistent with the values found in the literature for the US (see for example Beaudry and van Wincoop (1996), and Engelhardt and Kumar (2003)).

Table 2.3: Calibrated and estimated parameters

		Income groups		
		Low	Middle	High
Time preference rate	β	0.97	0.97	0.97
Depreciation rate	δ	0.07	0.07	0.07
Capital share	α	0.32	0.32	0.32
Mean growth rate	μ_g	1.0075	1.0075	1.0075
Steady-state normalized debt	$\bar{d}$	0.78	0.59	0.205
Risk aversion parameter	γ	12.7	2.08	1.01
Volatility of g shock	σ_g	0.010	0.0061	0.0042
Volatility of a shock	σ_a	0.016	0.0071	0.0050
Autocorrelation of g shock	ρ_g	0.19	0.60	0.25
Autocorrelation of a shock	ρ_a	0.75	0.90	0.82
Coefficient on interest rate premium	ψ	0.048	0.062	0.107
Capital adjustment cost parameter	ϕ	2.3	4.1	4.35

2.4.2 Business cycle moments: low- vs middle- vs high-income groups

For each of the income groups I present the major stylized features of macroeconomic fluctuations along with those of the model economy in Table 2.4 and Table 2.5. For the low-income group parameterization the model is successful as Table 2.4 shows: both qualitatively and quantitatively it replicates the features of actual data. It is able to almost perfectly replicate the moments I match: the strong negative correlation of savings and debt, acyclical trade balance, the volatility of the macro aggregates. The model performs well in terms of the rest of the stylized facts even though these are not explicitly matched in the estimation exercise.

For the middle- and high-income group parameterizations the model is quite successful: qualitatively, it replicates most of the features of actual data. The trade balance is more strongly countercyclical for the middle-income countries than for the high-income countries; and the volatility of consumption relative to output is higher for the middle-income group. These features are captured well in the model. Regarding investment, although quantitatively the model is unable to replicate the volatility of investment, it still mimics the fact that investment is more volatile than consumption and output.

Table 2.4: Moments: low-income countries

	Empirical moments	Model moments
$\rho(\frac{d}{y}, \frac{s}{y})$	-0.35	-0.35
$\rho(\frac{tb}{y}, y)$	-0.03	-0.03
$\sigma(y)$	0.062	0.062
$\sigma(c)/\sigma(y)$	1.16	1.16
$\sigma(i)/\sigma(y)$	3.69	3.28
$\sigma(\frac{d}{y})$	0.179	0.188
$\rho(y, i)$	0.58	0.57
$\rho(y, c)$	0.67	0.77
$\rho(y)$	0.78	0.95
$\rho(\Delta y)$	0.13	0.09
s/y	0.11	0.11
d/y	0.63	0.63

2.5 Conclusion

This paper explores the business cycle regularities of low-income countries in comparison to those observed in middle- and high-income countries. The data reveals several distinguishing features of the business cycle in low-income countries compared to the other two income groups: acyclical trade balances; highest volatility of consumption relative to output; highest volatility of debt; highest average debt-to-output ratio and lowest average savings ratio; significant negative correlation between domestic saving rates and the net foreign asset position.

A small open economy model with both trend and transitory shocks to productivity, and varying intertemporal elasticity of substitution (IES), motivated by subsistence consumption theories, can be used to account for the distinguishing features of the three income groups. The theoretical model shows that while both permanent shocks and transitory fluctuations around the trend are important sources of

Table 2.5: Moments: middle and high-income countries

	Middle-income group		**High-income group**	
	Data	Model	Data	Model
$\rho(\frac{d}{y}, \frac{s}{y})$	-0.20	-0.20	-0.06	-0.06
$\rho(\frac{tb}{y}, y)$	-0.38	-0.38	-0.22	-0.22
$\sigma(y)$	0.0672	0.0672	0.0312	0.0312
$\sigma(c)/\sigma(y)$	1.11	1.11	1.02	1.02
$\sigma(i)/\sigma(y)$	3.37	2.26	3.47	2.41
$\sigma(\frac{d}{y})$	0.115	0.101	0.087	0.018
$\rho(y, i)$	0.78	0.91	0.82	0.83
$\rho(y, c)$	0.86	0.94	0.81	0.96
$\rho(y)$	0.84	0.98	0.80	0.97
$\rho(\Delta y)$	0.34	0.34	0.31	0.08
s/y	0.19	0.19	0.22	0.22
d/y	0.37	0.37	0.12	0.12

fluctuations in low-income countries, temporary shocks play a predominant role. In comparison to the other two income groups the volatility of the temporary shock for the low-income countries is more than three times higher than that for the high-income group and twice as large as that for the middle-income group. The same pattern holds for the permanent shock.

Given the limited literature on business cycle fluctuations in low-income countries and the fact that the theoretical model I present in this paper is successful in replicating the distinguishing empirical regularities of the three income groups, the model can be used as a benchmark for studying the impact of changes in the external environment, such as world interest rates or structure and duration of shocks, as well as internal macroeconomic developments not only for low-income countries, but also for comparing them to the potential outcomes in the middle- and high-income groups.

Appendix A

Appendix to Chapter 1

A.1 Institutional variables

In the empirical analysis I use an expropriation risk variable that specifically measures the risk of expropriation or arbitrary contract modifications. The table below shows that the expropriation risk variable and three empirical indicators that capture different dimensions of of institutional quality (political stability, rule of law and control of corruption) are very highly correlated. Therefore, expropriation risk can be interpreted more broadly as a measure of public governance, which can include bureaucratic corruption, deviations from rule of law, arbitrary government regulations.

- **Expropriation Risk:** combines risk of unilateral contract modification or expropriation; restrictions on profit repatriation; and payment delays by government. Source: International country risk guide, 2007;

- **Political Stability:** captures the likelihood that the government will be destabilized or overthrown by unconstitutional or violent means, including politically-motivated violence and terrorism. Source: Kaufmann et al., 2009;

- **Rule of Law:** captures the extent to which agents have confidence in and abide by the rules of society, and in particular the quality of contract enforcement, property rights, the police, and the courts, as well as the likelihood of crime and violence. Source: Kaufmann et al., 2009;

- **Control of Corruption:** captures the extent to which public power is exercised for private gain, including different forms of corruption. Source: Kaufmann et al., 2009.

Table A.1: Institutional variables: correlation matrix

	Expropr. risk	Political stab.	Rule of law	Control of corr.
Expropr. risk	1.00	0.81	0.84	0.85
Political stab.	0.81	1.00	0.89	0.85
Rule of law	0.84	0.89	1.00	0.97
Control of corr.	0.85	0.85	0.97	1.00

A.2 Total FDI and portfolio investment: summary statistics

Table A.2: FDI and portfolio liabilities as a ratio of total liabilities (mean 1995-2007)

All countries	Obs.	Mean	Median	St.Dev.
(FDI+PO)/Total	81	0.322	0.310	0.165
FDI/Total	81	0.250	0.230	0.144
PO/Total	81	0.072	0.039	0.096

Low-income countries	Obs.	Mean	Median	St.Dev.
(FDI+PO)/Total	26	0.195	0.168	0.112
FDI/Total	26	0.178	0.157	0.107
PO/Total	26	0.017	0.002	0.034

Middle-income countries	Obs.	Mean	Median	St.Dev.
(FDI+PO)/Total	29	0.375	0.360	0.152
FDI/Total	29	0.327	0.306	0.138
PO/Total	29	0.048	0.026	0.060

High-income countries	Obs.	Mean	Median	St.Dev.
(FDI+PO)/Total	26	0.387	0.393	0.153
FDI/Total	26	0.236	0.203	0.146
PO/Total	26	0.152	0.123	0.116

FDI: FDI liabilities
PO: Portfolio investment liabilities
Total: Total liabilities including FDI, PO and Debt
Source data: Lane and Milesi-Ferretti (2009).

A.3 MLE estimation with a generated regressor

The model I estimate is:

$$Y = \gamma_0 + \gamma_1 \hat{\beta}_{mi} + \mathbf{Z}\,\mathbf{\Gamma_2} + \epsilon_i$$

where $\mathbf{Z}$ is the vector of control variables measured without error, and $\mathbf{\Gamma_2}$ is the coefficient vector associated with the control variables. Let the measurement error of the generated regressor be u_i:

$$\hat{\beta}_{mi} \;=\; \beta_{mi} \;+\; u_i$$

where the covariance risk variable β_{mi} is the true variable, while $\hat{\beta}_{mi}$ is the estimated or observed variable. The idea behind the adjusted estimator is to choose (γ_0, γ_1) to minimize the quadratic form $\eta'\Omega^{-1}\eta$ where:

$$\eta_{\mathbf{i}} = \begin{pmatrix} \epsilon_i \\ u_i \end{pmatrix} = \begin{pmatrix} Y_i - \gamma_0 - \gamma_1\beta_{mi} - \mathbf{Z_i}\,\mathbf{\Gamma_2} \\ \hat{\beta}_{mi} - \beta_{mi} \end{pmatrix} \sim N(0, \Omega)$$

$$\mathbf{\Omega} = \begin{bmatrix} \Sigma_\epsilon & 0 \\ 0 & \Sigma_u \end{bmatrix}$$

where Σ_ϵ is the covariance matrix of the residuals from the cross-sectional regression regression; and Σ_u is the covariance matrix of the measurement error in $\hat{\beta}_{mi}$.

The MLE is a function of δ: the relative magnitude of the error variances of Y and $\hat{\beta}_{mi}$. Without additional information about the error terms, ϵ and u, the MLE of the unknown parameter vector that minimizes the likelihood function does not exist. Fuller (1987) assumes the relative magnitude of the error variances is known, while Kim (1995) derives it for the two-pass estimation of expected returns. Since in my case the relative variance is neither known nor can be easily derived from the model, I get Σ_u and Σ_ϵ using a bootstrap procedure and set δ equal to the median of the diagonal of $\Sigma_u^{-1}\Sigma_\epsilon$. In what follows I use the simulated relative variances and apply the correction proposed Kim (1995). The MLE of γ_1, $\mathbf{\Gamma_2}$, and γ_0 are given by:

$$\hat{\gamma}_1 = \frac{S + \left[S^2 + 4\delta\Big(m_{Y\hat{\beta}_{mi}} - \mathbf{M}'_{\hat{\beta}_{mi}\mathbf{Z}}\mathbf{M}^{-1}_{\mathbf{ZZ}}\mathbf{M}_{Y\mathbf{Z}}\Big)^2\right]^{1/2}}{2\Big(m_{Y\hat{\beta}_{mi}} - \mathbf{M}'_{\hat{\beta}_{mi}\mathbf{Z}}\mathbf{M}^{-1}_{\mathbf{ZZ}}\mathbf{M}_{Y\mathbf{Z}}\Big)}$$

$$\hat{\mathbf{\Gamma}}_\mathbf{2} = \mathbf{M}^{-1}_{\mathbf{ZZ}}\mathbf{M}'_{Y\mathbf{Z}} - \mathbf{M}^{-1}_{\mathbf{ZZ}}\mathbf{M}'_{\hat{\beta}_{mi}\mathbf{Z}}\hat{\gamma}_1$$

$$\hat{\gamma}_0 = E[Y] - \hat{\gamma}_1\, E[\hat{\beta}_{mi}] - E[\mathbf{Z}]\,\hat{\mathbf{\Gamma}}_\mathbf{2}$$

where:

$$S = m_{YY} - \mathbf{M}'_{Y\mathbf{Z}}\mathbf{M}^{-1}_{\mathbf{ZZ}}\mathbf{M}_{Y\mathbf{Z}} - \delta\Big(m_{\hat{\beta}_{mi}\hat{\beta}_{mi}} - \mathbf{M}'_{\hat{\beta}_{mi}\mathbf{Z}}\mathbf{M}^{-1}_{\mathbf{ZZ}}\mathbf{M}_{\hat{\beta}_{mi}\mathbf{Z}}\Big)$$

and m_{xy} and $\mathbf{M}_{xy}$ are the second co-moment between variables x and y (the boldface represents a vector or a matrix). Let $\hat{\mathbf{\Gamma}} = (\gamma_0, \gamma_1, \mathbf{\Gamma_2})$, then Kim (1995) shows that the asymptotic distribution of $\hat{\mathbf{\Gamma}}$ is given by:

$$\sqrt{N}(\hat{\mathbf{\Gamma}} - \mathbf{\Gamma}) \to N(\mathbf{0}, \mathbf{\Sigma}_{\hat{\mathbf{\Gamma}}})$$

$$\mathbf{\Sigma}_{\hat{\mathbf{\Gamma}}} = \begin{bmatrix} (1+\mu_z'\Sigma_{zz}^{-1}\mu_z)\sigma_w^2 + \phi^2\sigma^2_{\hat{\gamma}_1} & -\phi\sigma^2_{\hat{\gamma}_1} & -\sigma_w^2\Sigma_{zz}^{-1}\mu_z + \phi\Sigma_{zz}^{-1}\Sigma_{\beta_{mi}z}\sigma^2_{\hat{\gamma}_1} \\ -\phi\sigma^2_{\hat{\gamma}_1} & \sigma^2_{\hat{\gamma}_1} & -\Sigma'_{\beta_{mi}z}\Sigma_{zz}^{-1}\sigma^2_{\hat{\gamma}_1} \\ -\sigma_w^2\Sigma_{zz}^{-1}\mu_z + \phi\Sigma_{zz}^{-1}\Sigma_{\beta_{mi}z}\sigma^2_{\hat{\gamma}_1} & -\Sigma_{zz}^{-1}\Sigma_{\beta_{mi}z}\sigma^2_{\hat{\gamma}_1} & \sigma_w^2\Sigma_{zz}^{-1} + \Sigma_{zz}^{-1}\Sigma_{\beta_{mi}z}\Sigma'_{\beta_{mi}z}\Sigma_{zz}^{-1}\sigma^2_{\hat{\gamma}_1} \end{bmatrix},$$

$$\sigma^2_{\hat{\gamma}_1} \equiv Var(\hat{\gamma}_1) = (\sigma^2_{\beta_{mi}} - \Sigma'_{\beta_{mi}z}\Sigma_{zz}^{-1}\Sigma_{\beta_{mi}z})^{-2}[(\sigma^2_{\beta_{mi}} - \Sigma'_{\beta_{mi}z}\Sigma_{zz}^{-1}\Sigma_{\beta_{mi}z})\sigma_w^2 + \delta\sigma_u^2],$$

$$\sigma_w^2 = (\delta + \gamma_1^2)\sigma_u^2, \qquad \phi = \mu_{\beta_{mi}} - \mu_z' \Sigma_{zz}^{-1} \Sigma_{\beta_{mi} z},$$

$$\text{and} \qquad (\mu_{\beta_{mi}}, \mu_z) \qquad \text{and} \qquad \begin{bmatrix} \sigma_{\beta_{mi}}^2 & \Sigma_{\beta_{mi} z}' \\ \Sigma_{\beta_{mi} z} & \Sigma_{zz} \end{bmatrix}$$

are the mean vector and variance matrix of β_{mi} and explanatory variables $\mathbf{Z}$. The variance matrix, $\Sigma_{\hat{\Gamma}}$ is estimated by replacing the unknown parameters with their sample estimates:

$$\hat{\sigma}_{\beta_{mi}}^2 = (2\delta)^{-1}\{[S^2 + 4\delta(m_{y\hat{\beta}_{mi}} - \mathbf{M}_{\hat{\beta}_{mi} z}' \mathbf{M}_{zz}^{-1} \mathbf{M}_{yz})^2]^{1/2} - S\}$$

$$\hat{\sigma}_u^2 = (2\delta)^{-1}\{\bar{S} - [S^2 + 4\delta(\mu_{y\hat{\beta}_{mi}} - M_{\hat{\beta}_{mi} z}' M_{zz}^{-1} M_{yz})^2]^{1/2}\}$$

where:

$$\bar{S} = S + 2\delta(\sigma_{\hat{\beta}_{mi}}^2 - M_{\hat{\beta}_{mi} z}' M_{zz}^{-1} M_{yz})$$

Appendix B

Appendix to Chapter 2

B.1 Debt stock data

This Appendix outlines the data construction process used by Lane and Milesi-Feretti (2001, 2006). The net external position (NFA) of a country is obtained by adding up the individual stock estimates for debt, portfolio equity, FDI and reserves using the accounting equation:

$$NFA_t = FDIA_t^* + EQA_t^* + DEBTA_t^* + FX_t - FDIL_t^* + EQL_t^* + DEBTL_t^*$$

where NFA is the net external position of a country, $DEBTA^*(L)$: debt assets (liabilities), $FDIA^*(L)$: stock of direct investment, $EQA^*(L)$: portfolio equity, FX: foreign exchange reserves.

In the absence of measures for all external assets and liabilities on the right-hand side of the above equation NFA is estimated using balance of payments data on current account and capital flows. Using the components of the capital and financial account, the measure of debt (assets: DEBTA, liabilities: DEBTL) is obtained as a residual:

$$\Delta DEBTL = -(\Delta PDL + \Delta OL + \Delta IMF + \Delta EF)$$

$$\Delta DEBTA = -(\Delta PDA + \Delta OA + EO)$$

where PDA(L): portfolio investment debt assets (liability), EF: exceptional financing, IMF: IMF credit and loans, KA: capital account, OA(L): other assets and liabilities, EO: errors and omissions. Errors and omissions are assumed to reflect unrecorded change of debt assets held abroad (capital flight).

Cumulative current account (CA) between dates s and t:

$$\sum_{s}^{t} CA = EQ_s(t) + FDI_s(t) + DEBTA_s(t) - DEBTL_s(t) - KA_s(t) + FX_s(t)$$

where for each variable $X_s(t)$ is the cumulative value of ΔX between s and t. Then the net external position becomes:

$$NFA(t) \approx NFA(s-1) + \sum_{s}^{t} CA + KA_s(t) =$$

Lane and Milesi-Feretti use the following major additional considerations and adjustments to the data:

- Account for debt reduction and debt forgiveness;
- Valuation: price and exchange rate changes impact value of assets and liabilities but are not captured in flows data.

B.2 Analytical HP filtering of model moments

The general solution of the detrended problem follows Schmitt-Grohe and Uribe (2004):

$$z_t = g(x_t, \sigma)$$

$$x_{t+1} = h(x_t, \sigma) + \sigma\epsilon_{t+1}$$

where z_t are the control variables and x_t: the state variables. For $\hat{x}_t \equiv x_t - x$, where x is the steady state, linear state-space form:

$$\hat{z}_t = g_x(x, 0)\hat{x}_t + g_\sigma(x, 0)\sigma$$

$$\hat{x}_{t+1} = h_x(x, 0)\hat{x}_t + h_\sigma(x, 0)\sigma + \sigma\epsilon_{t+1}$$

Variance-covariance matrix of the state vector $\hat{x}_t$:

$$E\{\hat{x}_t\hat{x}'_t\} = h_x\Sigma_X h'_x + \sigma^2 \equiv \Sigma_X$$

$$E\{\hat{x}_t\hat{x}'_{t-j}\} = h_x^j\Sigma_X$$

$$E\{\hat{z}_t\hat{z}'_{t-j}\} = g_x E\{\hat{x}_t\hat{x}'_{t-j}\}g'_x$$

I am interested in the moments of HP-filtered data from the model to correspond to the empirical moments. Therefore, I need to map the moments of the hatted variables to the moments of the HP-filtered "non-hatted" variables. The solution method allows us to analytically find the moments of the variables of interest that are directly comparable to the data moments:

$$\hat{y}_t \approx ln(y_t/y) = ln((Y_t/\Gamma_{t-1})/y) = ln(Y_t) - ln(y) - ln(\Gamma_{t-1})$$

Non-hatted control variables:

1. Log levels:

$$ln(Y_t) = \hat{y}_t + ln(y) + ln(\Gamma_{t-1})$$

2. Ratios:

$$ln(C_t/Y_t) = \frac{\hat{c}_t}{y_t} + ln(c/y)$$

3. First differenced log levels:

$$ln(Y_t) - ln(Y_{t-1}) = \frac{\hat{y}_t}{\hat{y}_{t-1}} g_{t-1}$$

Therefore, no transformation necessary for hatted ratios and growth rates. Recall $\hat{z}_t$ is the vector of hatted control variables; denote $\bar{\hat{z}}_t$ the desired non-hatted control variables whose moments can be directly comparable to the data moments.

$$\bar{\hat{\mathbf{z}}}_{\mathbf{t}} = \begin{pmatrix} ln(Y_t) \\ ln(C_t) \\ ln(I_t) \\ \frac{S_t}{Y_t} \\ \frac{D_t}{Y_t} \\ ln(\frac{I_t}{Y_t}) \\ \frac{TB_t}{Y_t} \\ \frac{CA_t}{Y_t} \\ ln(\frac{C_t}{Y_t}) \\ ln(Y_t) - ln(Y_{t-1}) \end{pmatrix}$$

n_s: number of states, n_c: number of controls. Let C_1 be n_c by n_s matrix with its last column containing 1 only for the log level variables and all other elements 0.

$$\mathbf{\hat{z}_t} = \begin{pmatrix} \hat{tb}_t \\ \hat{y}_t \\ \hat{c}_t \\ \hat{i}_t \\ \hat{ca}_t \\ \hat{s}_t \\ \hat{\frac{s}{y}}_t \\ \hat{\frac{d}{y}}_t \\ \hat{\frac{iv}{y}}_t \\ \hat{\frac{tb}{y}}_t \\ \hat{\frac{ca}{y}}_t \\ \hat{\frac{c}{y}}_t \\ \frac{\hat{y}_t}{\hat{y}_{t-1}} g_{t-1} \end{pmatrix} \qquad \mathbf{C_1} = \begin{pmatrix} 0 & 0 & \dots & 0 & 1 \\ 0 & 0 & \dots & 0 & 1 \\ 0 & 0 & \dots & 0 & 1 \\ 0 & 0 & \dots & 0 & 0 \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ 0 & 0 & \dots & 0 & 0 \end{pmatrix} \qquad \mathbf{\hat{x}_t} = \begin{pmatrix} \frac{\hat{y}_{t-1}}{\hat{y}_{t-2}} g_{t-2} \\ \hat{y}_{t-1} \\ \hat{k}_t \\ a_t \\ g_t \\ \hat{\Gamma}_t \end{pmatrix}$$

Then the variables of interest (ignoring the steady states since I am primarily interested in the second moments) are: $\bar{\hat{z}}_t = \hat{z}_t + C_1\hat{x}_{t-1}$. From the general solution of the model $\hat{z}_t = g_x\hat{x}_t$, then:

$$\bar{\hat{z}}_t = g_x\hat{x}_t + C_1\hat{x}_{t-1}$$

Then the variance-covariance matrix of the new control variables is:

$$E\{\bar{\hat{z}}_t\bar{\hat{z}}_t'\} = g_x E\{\hat{x}_t\hat{x}_t'\}g_x' + C_1 E\{\hat{x}_{t-1}\hat{x}_{t-1}'\}C_1' + g_x h_x E\{\hat{x}_t\hat{x}_{t-1}'\}C_1' + C_1 E\{\hat{x}_{t-1}\hat{x}_t'\}g_x'$$

Use $E\{\hat{x}_t\} = h_x\hat{x}_{t-1}$:

$$E\{\bar{\hat{z}}_t\bar{\hat{z}}_t'\} = g_x\Sigma_X g_x' + C_1\Sigma_X C_1' + g_x h_x\Sigma_X C_1' + C_1\Sigma_X h_x' g_x'$$

Next I follow Burnside (1999) and HP-filter the desired new series from the model by applying the filter B(L) to $\bar{\hat{z}}_t$. I follow McElroy (2008) to calculate HP-filter coefficients.

B.3 Additional Tables

Table B.1: Country List

Low-income group	Middle-income group	High-income group
Bangladesh	Argentina	Australia
Benin	Botswana	Austria
Bolivia	Brazil	Belgium
Burkina Faso	Chile	Brunei
Cameroon	China	Canada
Chad	Colombia	Denmark
Congo, Dem. Rep.	Costa Rica	Estonia
Congo, Rep.	Dominican Republic	Finland
Cote d'Ivoire	Ecuador	France
Ethiopia	Egypt, Arab Rep.	Germany
Ghana	El Salvador	Greece
Guinea	Fiji	Hungary
Haiti	Gabon	Iceland
Honduras	Guatemala	Ireland
India	Jamaica	Israel
Indonesia	Jordan	Italy
Kenya	Malaysia	Japan
Madagascar	Mauritius	Korea, Rep.
Malawi	Mexico	Netherlands
Mozambique	Morocco	New Zealand
Nepal	Namibia	Norway
Nicaragua	Panama	Portugal
Pakistan	Paraguay	Saudi Arabia
Papua New Guinea	Philippines	Singapore
Rwanda	South Africa	Slovenia
Senegal	Syrian Arab Rep.	Spain
Sri Lanka	Thailand	Sweden
Sudan	Tunisia	Switzerland
Tanzania	Turkey	United Kingdom
Togo	Uruguay	United States
Uganda		
Yemen, Rep.		
Zambia		

Table B.2: Empirical moments I: low-income countries

	$\rho(\frac{d}{y}, \frac{s}{y})$	$\rho(\frac{tb}{y}, y)$	$\rho(y)$	$\rho(\Delta y)$
Bangladesh	-.04 (.14)	-.02 (.13)	.81 (.12)	-.30 (.23)
Benin	-.32 (.08)	-.24 (.17)	.76 (.10)	.13 (.08)
Bolivia	-.44 (.20)	-.03 (.10)	.94 (.01)	.68 (.06)
Burkina Faso	-.02 (.22)	-.57 (.16)	.68 (.13)	-.19 (.09)
Cameroon	-.42 (.14)	-.12 (.12)	.94 (.02)	.39 (.22)
Chad	-.51 (.17)	.14 (.18)	.47 (.10)	-.11 (.21)
Congo, Dem. Rep.	.10 (.16)	-.06 (.09)	.92 (.02)	.58 (.12)
Congo, Rep.	-.61 (.12)	.62 (.06)	.66 (.06)	.10 (.15)
Cote d'Ivoire	-.54 (.13)	.13 (.13)	.83 (.03)	.45 (.16)
Ethiopia	.01 (.11)	-.50 (.09)	.60 (.06)	.01 (.07)
Ghana	.41 (.18)	-.42 (.13)	.90 (.04)	.27 (.15)
Guinea	-.20 (.31)	.21 (.16)	.83 (.03)	.07 (.12)
Haiti	-.60 (.13)	-.12 (.11)	.66 (.04)	.47 (.06)
Honduras	.47 (.15)	-.06 (.16)	.77 (.06)	.22 (.17)
India	-.38 (.09)	.33 (.24)	.81 (.05)	-.01 (.14)
Indonesia	-.36 (.12)	-.66 (.14)	.85 (.04)	.27 (.06)
Kenya	.42 (.23)	-.12 (.08)	.78 (.03)	.69 (.10)
Madagascar	-.30 (.23)	-.19 (.14)	.58 (.08)	-.18 (.12)
Malawi	-.53 (.12)	.77 (.03)	.42 (.19)	-.43 (.20)
Mozambique	-.83 (.06)	.16 (.18)	.83 (.03)	.45 (.11)
Nepal	-.48 (.11)	.57 (.20)	.55 (.07)	-.28 (.06)
Nicaragua	-.69 (.07)	.27 (.14)	.86 (.08)	.23 (.09)
Pakistan	-.43 (.14)	-.02 (.13)	.90 (.03)	.25 (.07)
Papua New Guinea	-.34 (.18)	.66 (.10)	.84 (.03)	.37 (.10)
Rwanda	-.35 (.08)	.71 (.16)	.47 (.19)	-.10 (.07)
Senegal	-.51 (.13)	-.01 (.24)	.59 (.20)	-.24 (.10)
Sri Lanka	-.21 (.17)	-.08 (.12)	.72 (.07)	.06 (.12)
Sudan	-.35 (.12)	-.27 (.11)	.80 (.04)	.32 (.19)
Tanzania	-.07 (.16)	-.20 (.24)	.86 (.02)	.88 (.02)
Togo	-.10 (.13)	-.48 (.09)	.57 (.04)	.00 (.08)
Uganda	-.32 (.11)	.36 (.18)	.89 (.02)	.58 (.08)
Yemen, Rep.	-.16 (.09)	.08 (.18)	.39 (.08)	-.17 (.09)
Zambia	-.40 (.17)	-.16 (.17)	.74 (.09)	.06 (.17)

Notes: GMM estimated standard errors are reported in parentheses. Data filtering is described in the text.

Table B.3: Empirical moments II: low-income countries

	$\sigma(\frac{d}{y})$	$\sigma(y)$	$\sigma(c)/\sigma(y)$	$\sigma(i)/\sigma(y)$
Bangladesh	.05 (.01)	.04 (.00)	1.07 (.18)	4.59 (1.31)
Benin	.17 (.02)	.05 (.00)	.98 (.14)	7.29 (.87)
Bolivia	.18 (.04)	.08 (.01)	.78 (.06)	3.06 (.44)
Burkina Faso	.07 (.01)	.04 (.01)	1.84 (.12)	3.94 (.91)
Cameroon	.20 (.03)	.17 (.03)	.83 (.07)	2.25 (.13)
Chad	.16 (.02)	.10 (.02)	1.48 (.26)	3.69 (.65)
Congo, Dem. Rep.	.30 (.04)	.13 (.02)	1.25 (.20)	3.65 (.56)
Congo, Rep.	.50 (.08)	.05 (.01)	3.61 (.78)	4.36 (.87)
Cote d'Ivoire	.22 (.04)	.05 (.01)	2.01 (.44)	4.87 (.90)
Ethiopia	.23 (.05)	.08 (.01)	1.27 (.06)	2.61 (.25)
Ghana	.15 (.03)	.10 (.02)	.85 (.06)	3.47 (.56)
Guinea	.08 (.01)	.02 (.00)	3.07 (.21)	7.01 (1.75)
Haiti	.09 (.01)	.07 (.01)	2.66 (.44)	7.76 (.99)
Honduras	.24 (.04)	.05 (.01)	1.29 (.17)	4.86 (.92)
India	.06 (.01)	.05 (.01)	.69 (.06)	1.81 (.25)
Indonesia	.21 (.06)	.08 (.01)	.78 (.15)	3.04 (.16)
Kenya	.18 (.04)	.06 (.02)	1.16 (.15)	2.99 (.89)
Madagascar	.20 (.03)	.05 (.01)	1.37 (.17)	4.58 (.48)
Malawi	.30 (.06)	.07 (.00)	.98 (.12)	3.89 (.53)
Mozambique	.58 (.08)	.13 (.02)	.96 (.07)	1.11 (.20)
Nepal	.07 (.01)	.03 (.00)	2.35 (.58)	3.37 (.80)
Nicaragua	2.19 (.62)	.14 (.02)	.88 (.04)	2.50 (.38)
Pakistan	.07 (.01)	.05 (.00)	1.07 (.20)	1.97 (.17)
Papua New Guinea	.18 (.02)	.08 (.01)	1.05 0.23)	1.54 (.34)
Rwanda	.15 (.05)	.13 (.03)	1.90 (.52)	3.16 (.56)
Senegal	.15 (.03)	.04 (.01)	.93 (.15)	4.86 (.62)
Sri Lanka	.08 (.02)	.03 (.00)	5.66 (1.36)	5.54 (.93)
Sudan	.27 (.06)	.09 (.01)	1.10 (.14)	4.44 (.63)
Tanzania	.11 (.02)	.05 (.00)	1.14 (.18)	3.11 (.33)
Togo	.21 (.03)	.07 (.02)	1.23 (.15)	4.36 (.45)
Uganda	.15 (.04)	.07 (.01)	1.00 (.02)	1.61 (.32)
Yemen, Rep.	.51 (.10)	.03 (.00)	2.23 (.35)	7.33 (1.77)
Zambia	.64 (.12)	.06 (.01)	2.74 (.52)	6.80 (1.41)

Notes: GMM estimated standard errors are reported in parentheses. Data filtering is described in the text.

Table B.4: Empirical moments III: low-income countries

	$\rho(y,c)$	$\rho(y,i)$	mean(s/y)	mean(d/y)
Bangladesh	.65 (.07)	-.08 (.08)	.16 (.01)	.28 (.01)
Benin	.56 (.10)	.54 (.13)	.05 (.01)	.51 (.05)
Bolivia	.96 (.01)	.64 (.06)	.15 (.01)	.73 (.04)
Burkina Faso	.86 (.08)	-.20 (.13)	.08 (.01)	.21 (.02)
Cameroon	.92 (.01)	.95 (.01)	.14 (.01)	.45 (.05)
Chad	.56 (.12)	0.43 (.16)	.00 (.02)	.64 (.07)
Congo, Dem. Rep.	.81 (.04)	.57 (.09)	.06 (.01)	.91 (.15)
Congo, Rep.	.07 (.34)	.55 (.14)	.13 (.03)	2.24 (.13)
Cote d'Ivoire	.60 (.07)	.64 (.05)	.09 (.02)	1.24 (.06)
Ethiopia	.89 (.05)	.79 (.07)	.15 (.01)	.51 (.06)
Ghana	.89 (.05)	.74 (.06)	.10 (.01)	.62 (.06)
Guinea	.92 (.02)	-.50 (.06)	.12 (.01)	.86 (.02)
Haiti	.21 (.18)	-.02 (.21)	.14 (.02)	.21 (.03)
Honduras	.79 (.07)	.44 (.14)	.16 (.01)	.63 (.05)
India	.88 (.04)	.68 (.06)	.22 (.01)	.17 (.01)
Indonesia	.60 (.18)	.95 (.02)	.26 (.01)	.53 (.05)
Kenya	.59 (.19)	-.13 (.14)	.16 (.01)	.48 (.04)
Madagascar	.80 (.04)	.86 (.03)	.06 (.01)	.65 (.07)
Malawi	.65 (.08)	-.64 (.11)	.02 (.02)	1.17 (.09)
Mozambique	.93 (.06)	.66 (.16)	-.07 (.02)	1.20 (.13)
Nepal	-.09 (.08)	-.05 (.15)	.18 (.01)	.18 (.03)
Nicaragua	.94 (.02)	.64 (.10)	.00 (.02)	2.21 (.42)
Pakistan	.69 (.05)	.89 (.02)	.21 (.01)	.44 (.01)
Papua New Guinea	.58 (.08)	.00 (.11)	.21 (.02)	.77 (.05)
Rwanda	.51 (.13)	.71 (.11)	.12 (.01)	.25 (.05)
Senegal	.49 (.11)	.56 (.20)	.06 (.01)	.56 (.04)
Sri Lanka	.27 (.18)	.68 (.07)	.18 (.01)	.43 (.02)
Sudan	.69 (.07)	.80 (.04)	.08 (.01)	.84 (.09)
Tanzania	.63 (.16)	.87 (.04)	.06 (.01)	.91 (.07)
Togo	.83 (.04)	.77 (.09)	.09 (.01)	.95 (.04)
Uganda	.99 (.01)	.29 (.10)	.06 (.01)	.47 (.03)
Yemen, Rep.	-.21 (.15)	.21 (.16)	.21 (.03)	.84 (.25)
Zambia	.67 (.07)	.58 (.07)	.02 (.01)	1.95 (.14)

Notes: GMM estimated standard errors are reported in parentheses. Data filtering is described in the text.

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Biography

Alexandra Tabova is a PhD candidate at Duke University and will complete her doctorate degree in economics in May 2011. In August 2011 she will join the Federal Reserve Board in Washington, DC as an Economist in the Division of International Finance. Her fields of specialization include international macroeconomics and international finance. Prior to pursuing a PhD Alexandra worked for three years in the Debt and Economic Policy Department and in the Financial Resource Mobilization Department at the World Bank. Alexandra was born in Perushtitsa, Bulgaria, and holds a Master's degree in economics from the Vrije Universiteit of Amsterdam, the Netherlands, and a Master's degree in international economic relations from the University of National and World Economy in Sofia, Bulgaria.